Advanced Data Structures and Algorithm Analysis

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浙江大学

Spring & Summer 2024
Lecture 3
2024-3-11

Outline:
Inverted File Index

- Information retrieval
- Index construction & compression
- Ranked retrieval
- Performance measures
- Take-home messages

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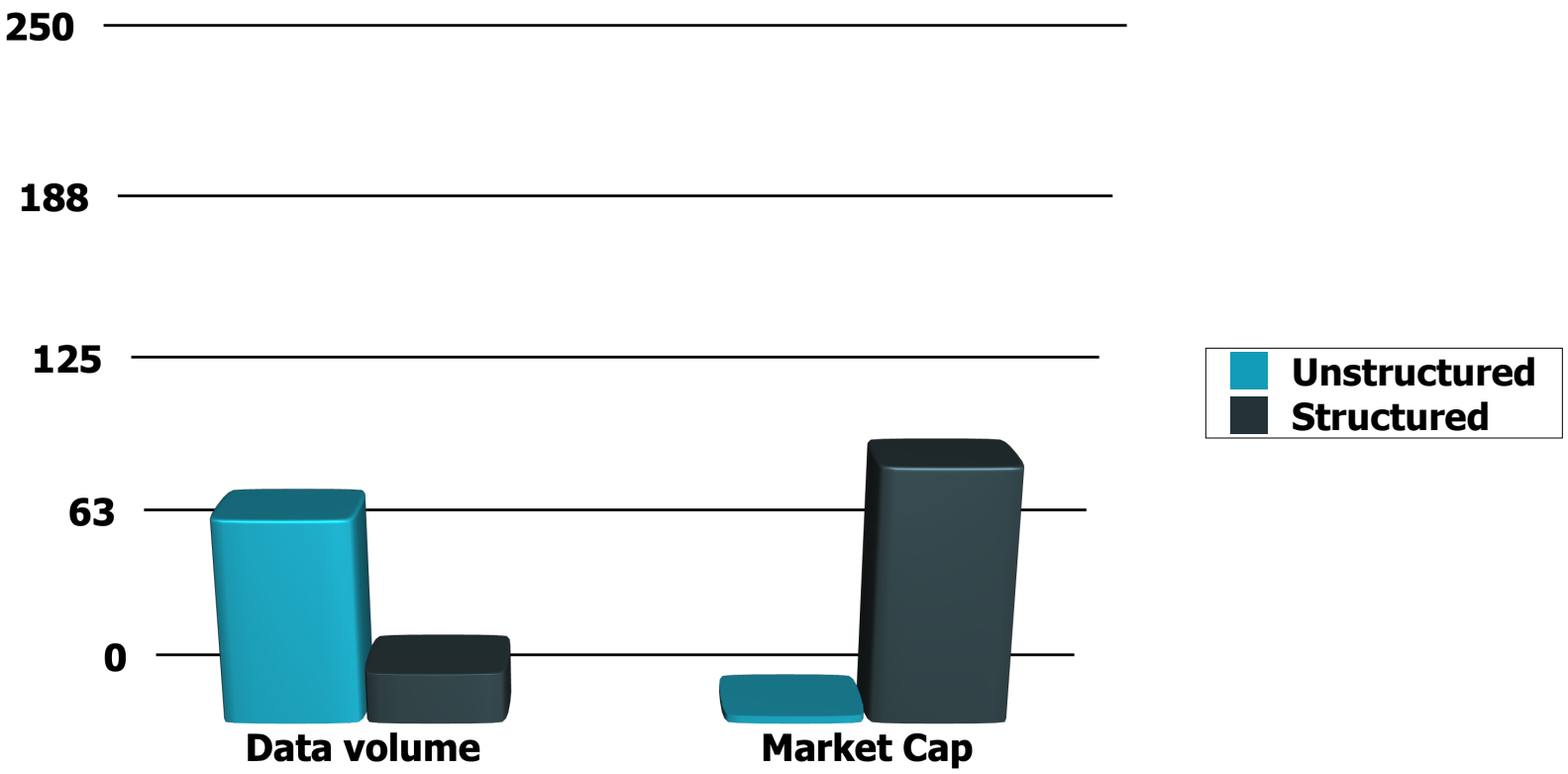
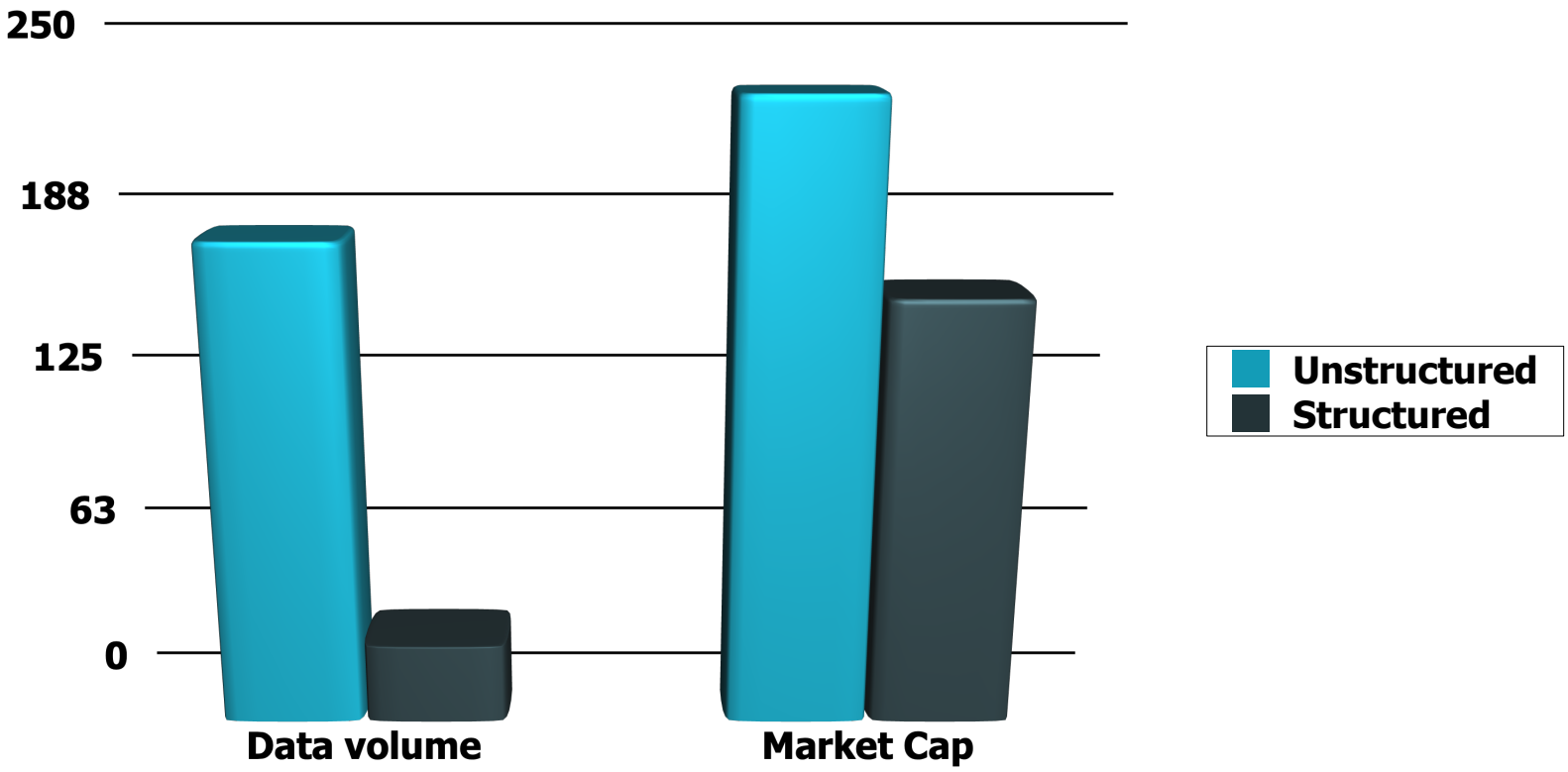
  - These days we frequently think first of web search, but there are many other cases:
    - E-mail search
    - Searching your laptop
    - Corporate knowledge bases
    - Legal information retrieval

Unstructured (text) vs. structured (database) data in the mid-nineties



Unstructured (text) vs. structured (database) data today



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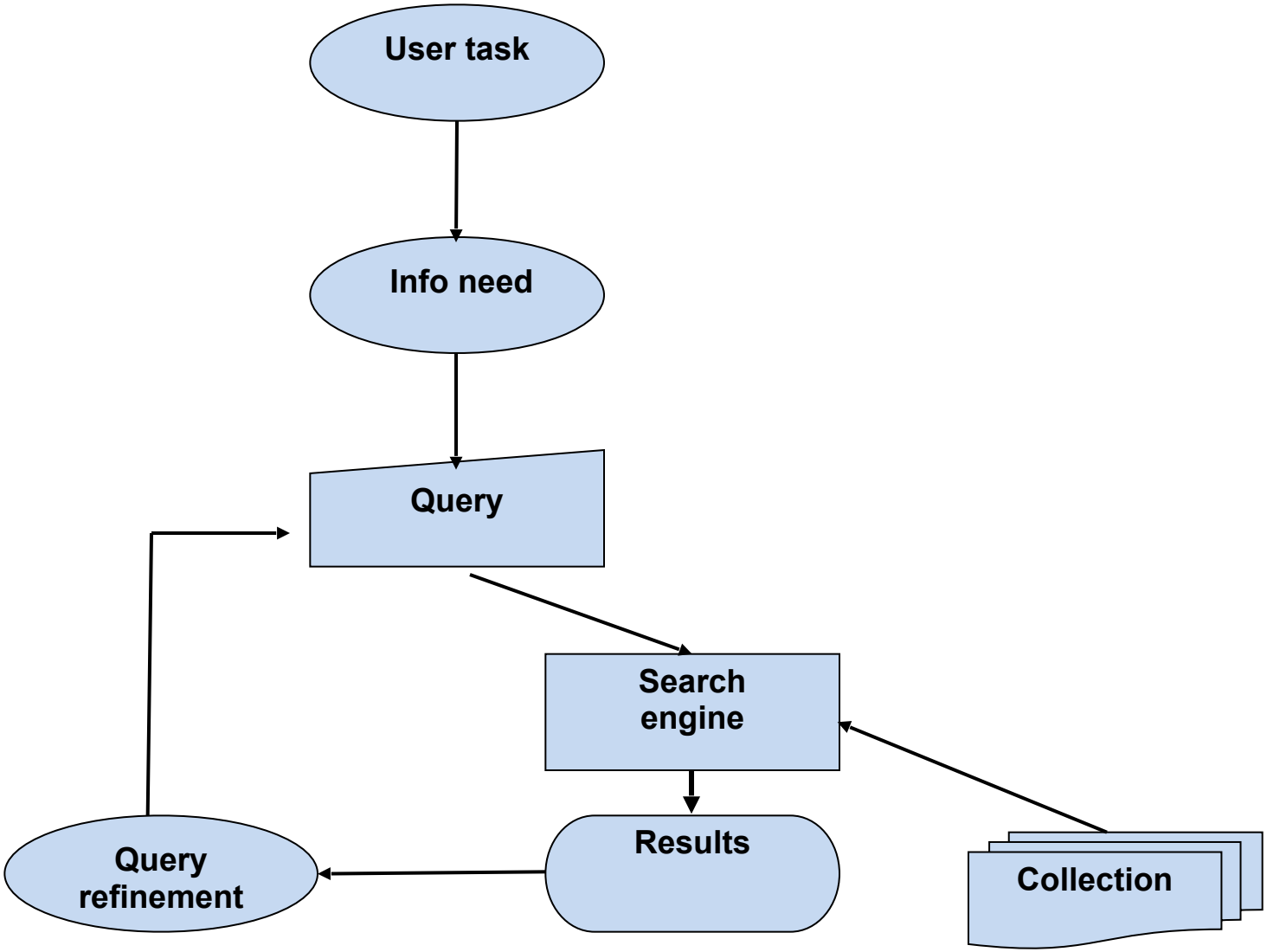
- Goal: Retrieve documents with information that is relevant to the user's information need and helps the user complete a task

The classic search model



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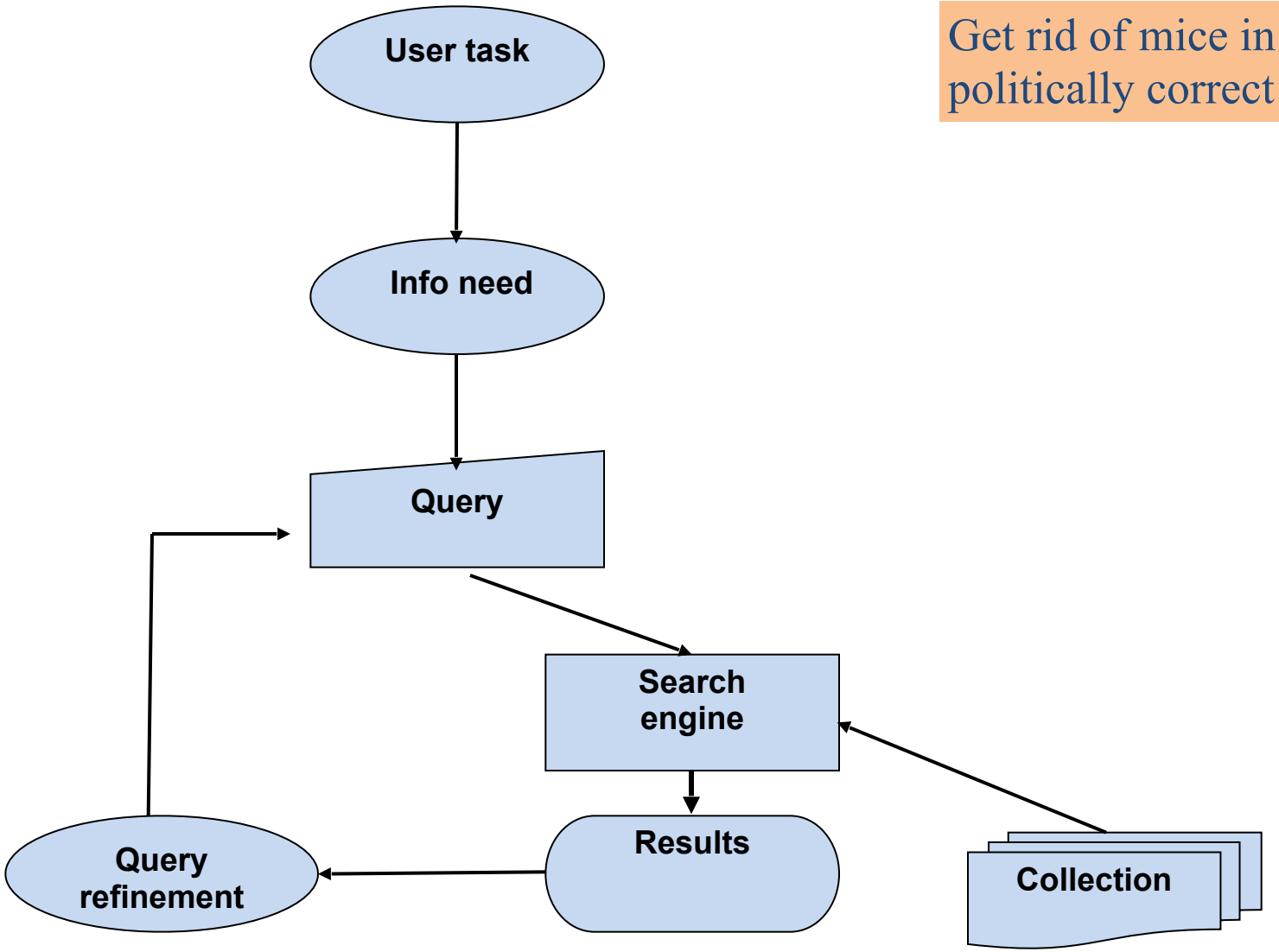

Get rid of mice in a politically correct way

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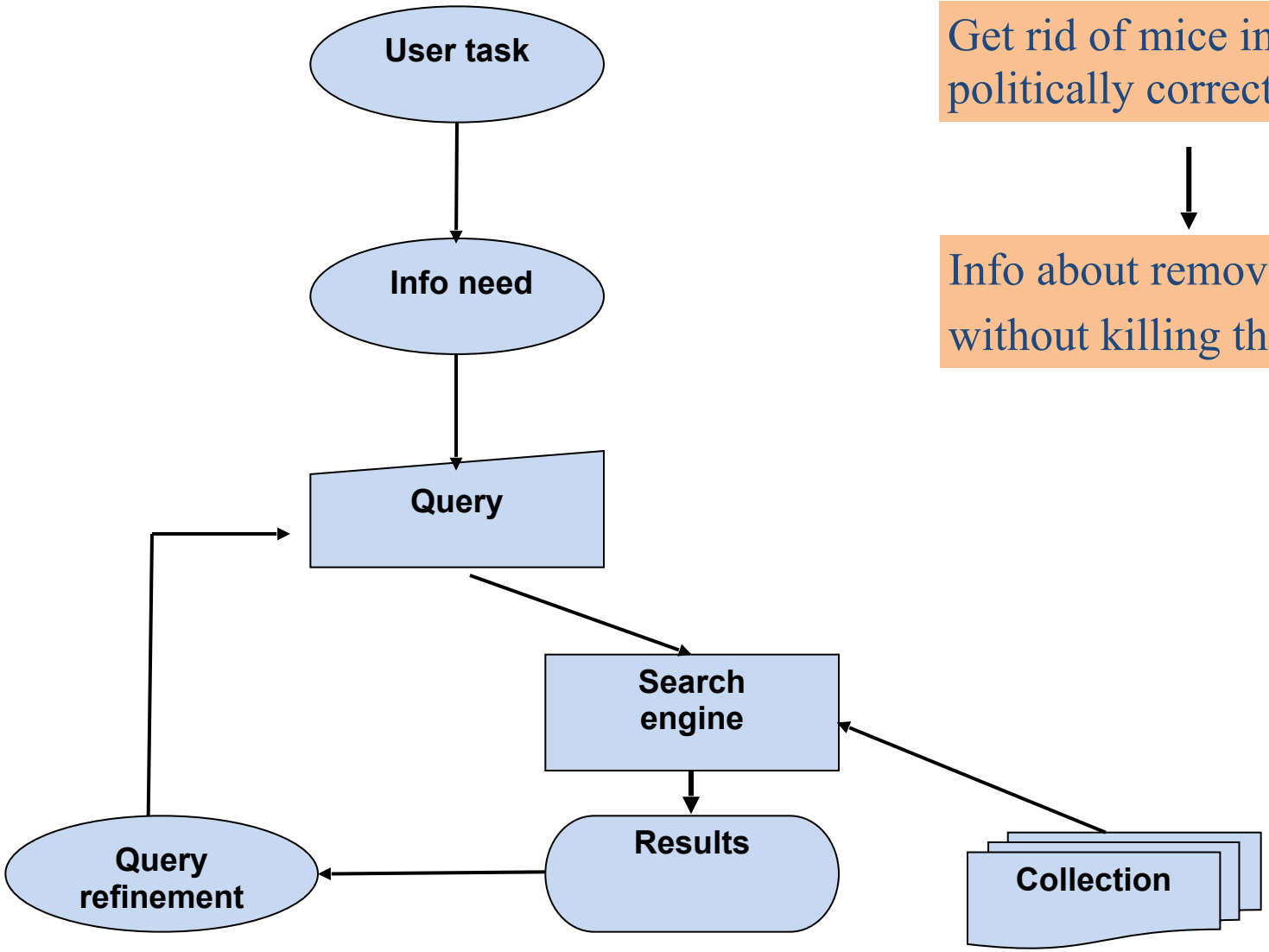

Get rid of mice in a politically correct way

Info about removing mice without killing them

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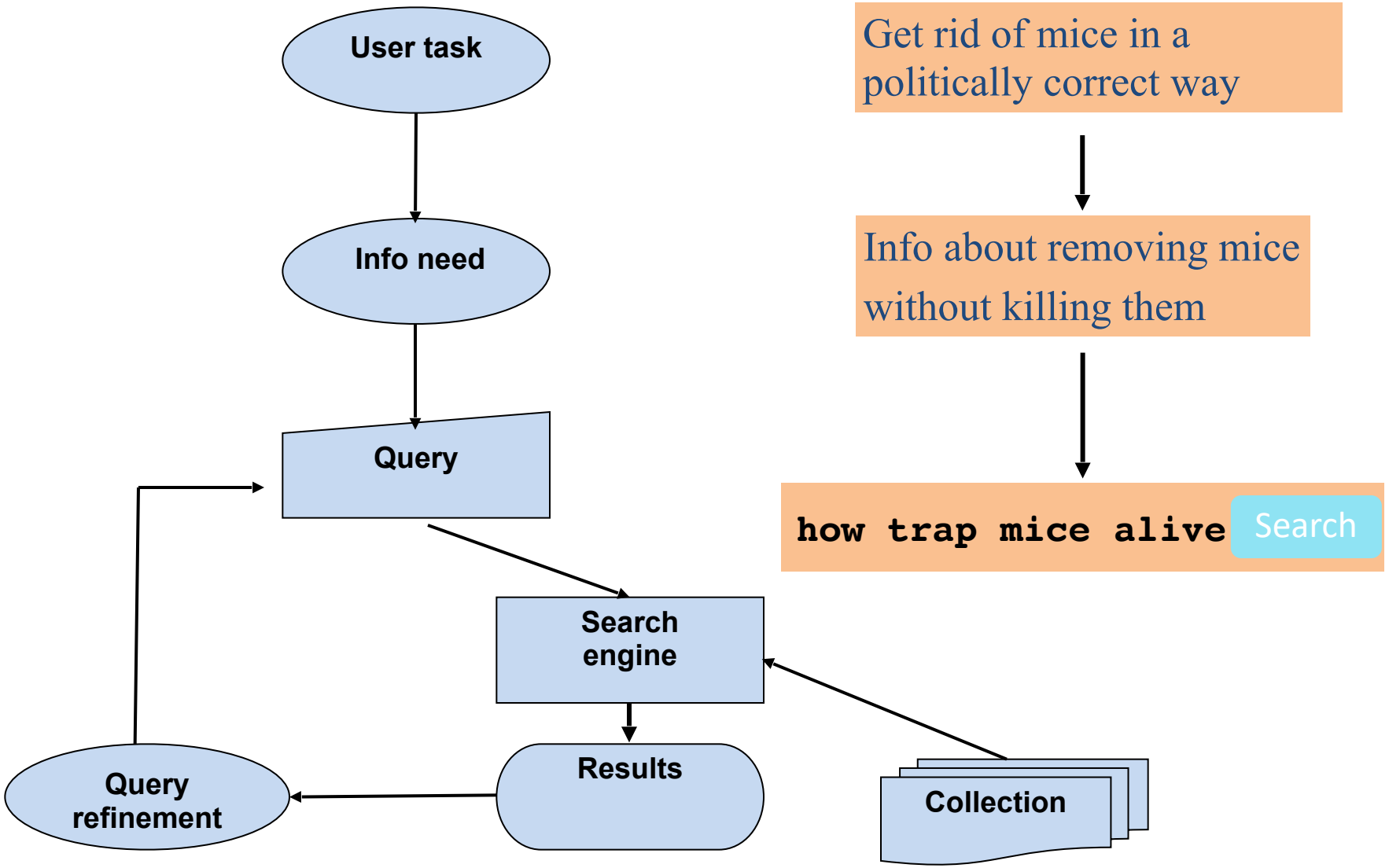

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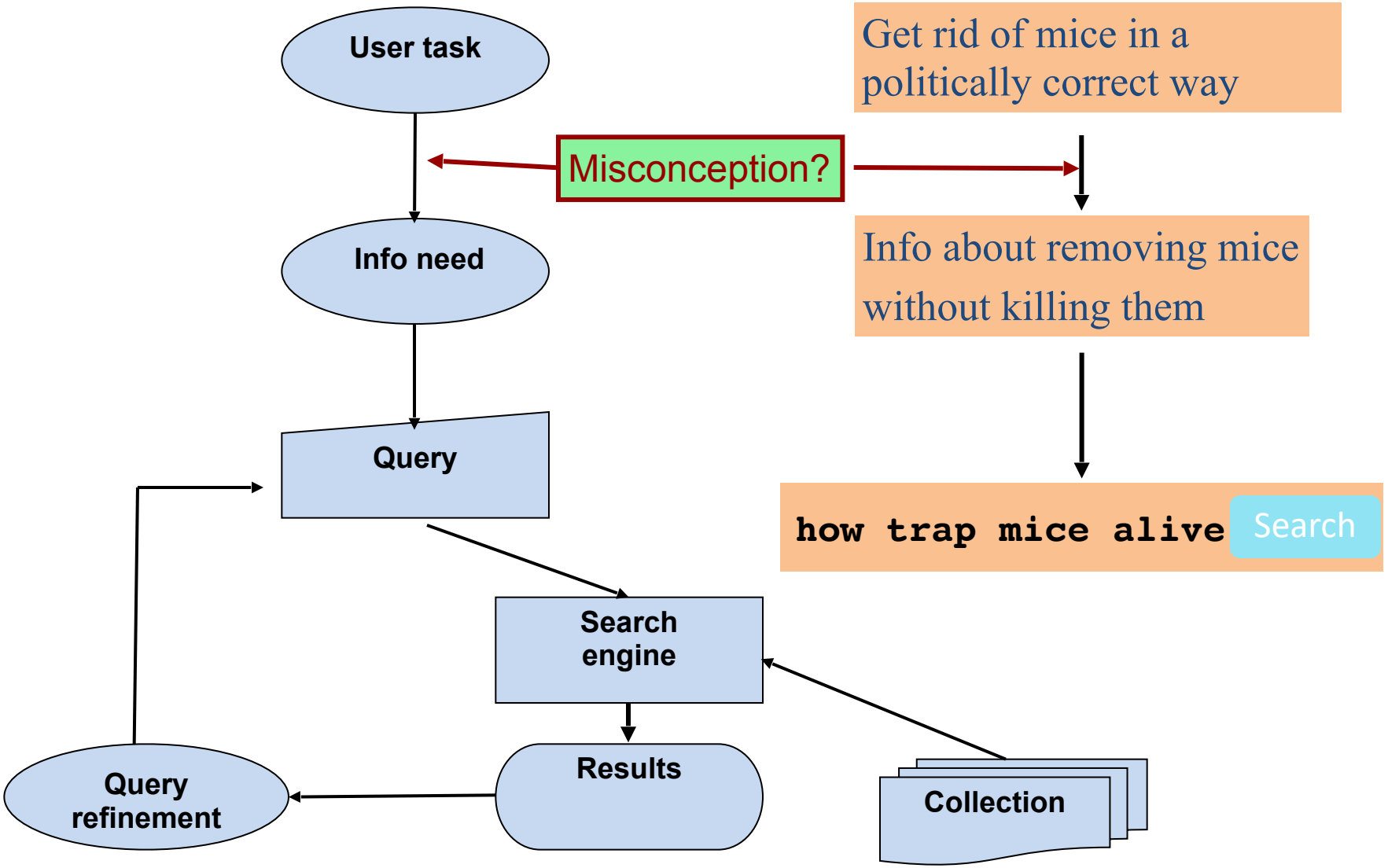

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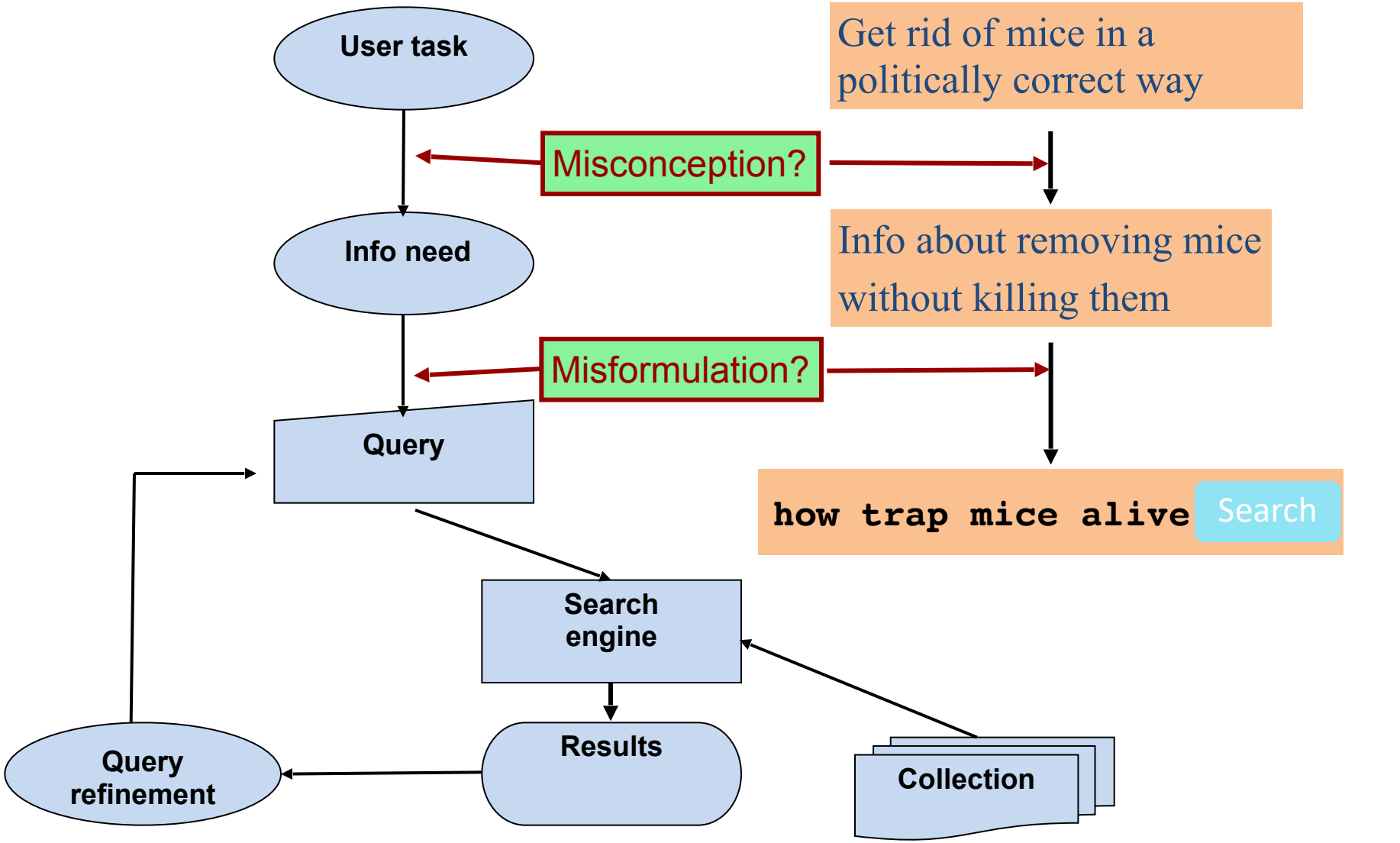

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- One could grep all of Shakespeare's plays for ***Brutus*** and ***Caesar,*** then strip out lines containing ***Calpurnia***?
- Why is that not the answer?
  - Slow (for large corpora)
  - *NOT* ***Calpurnia*** is non-trivial
  - Other operations (e.g., find the word ***Romans*** near ***countrymen***) not feasible
  - Ranked retrieval (best documents to return)
    - Later in the course

Term-document incidence matrices

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

1 if play contains word, 0 otherwise

Brutus *AND* ***Caesar*** *BUT NOT* ***Calpurnia***

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Answers to query

- Antony and Cleopatra, Act III, Scene ii

Agrippa [Aside to DOMITIUS ENOBARBUS]: Why, Enobarbus,
When Antony found Julius ***Caesar*** dead,
He cried almost to roaring; and he wept
When at Philippi he found ***Brutus*** slain.

- Hamlet, Act III, Scene ii

Lord Polonius: I did enact Julius ***Caesar*** I was killed i' the Capitol; ***Brutus*** killed me.

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- Avg 6 bytes/word including spaces/punctuation
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- Say there are *M* = 500K *distinct* terms among these.

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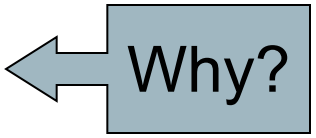

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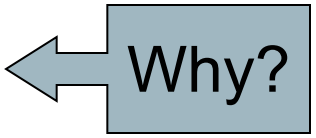
- What's a better representation?
  - We only record the 1 positions.



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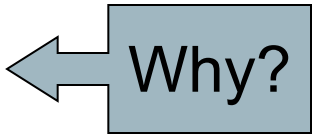

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For one term, better to retrieval it only in documents indeed having it.
Build lists of documents for each term: inverted index.

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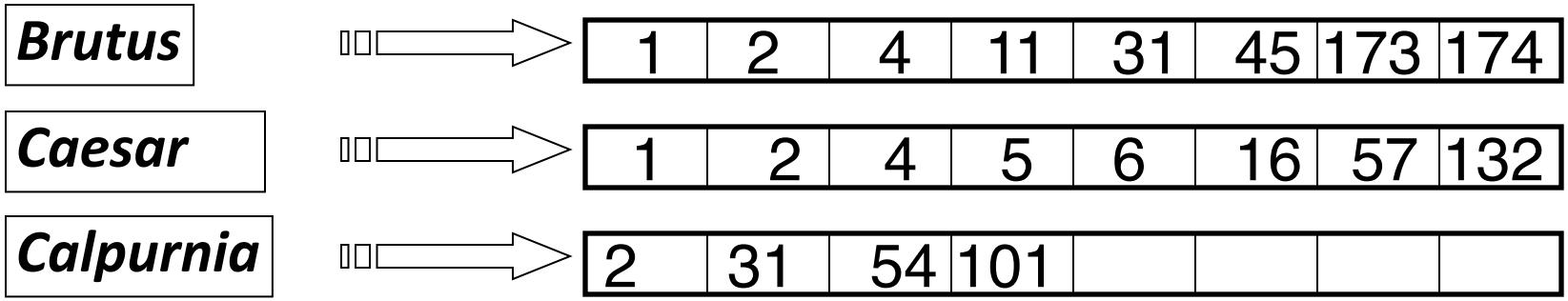

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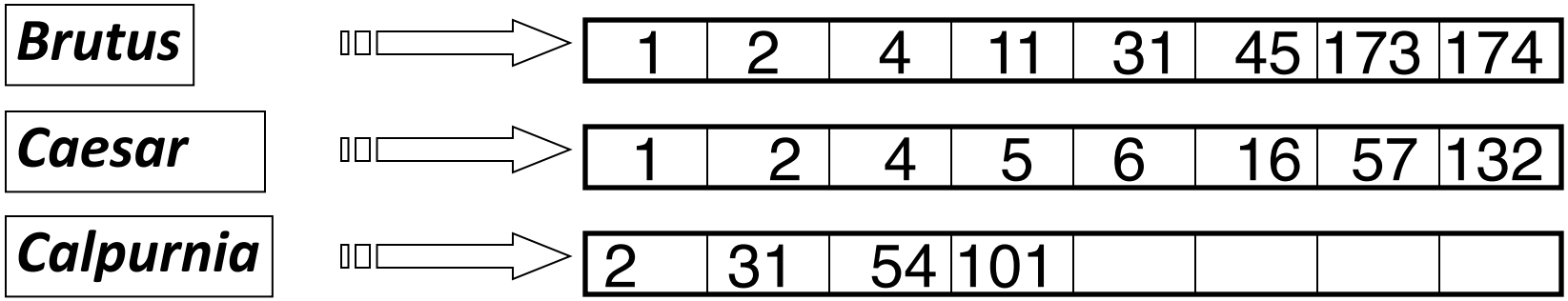
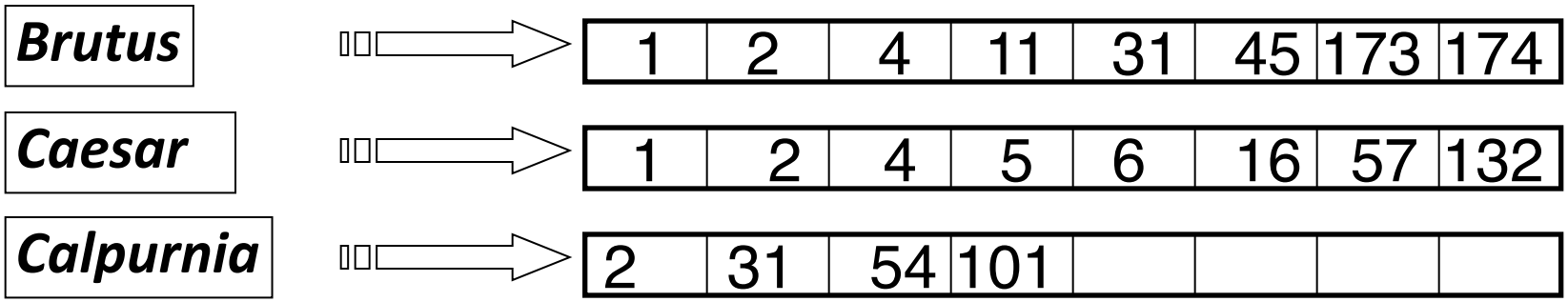


What happens if the word ***Caesar*** is added to document 14?

Inverted index

- We need variable-size postings lists
  - On disk, a continuous run of postings is normal and best
  - In memory, can use linked lists or variable length arrays
    - Some tradeoffs in size/ease of insertion



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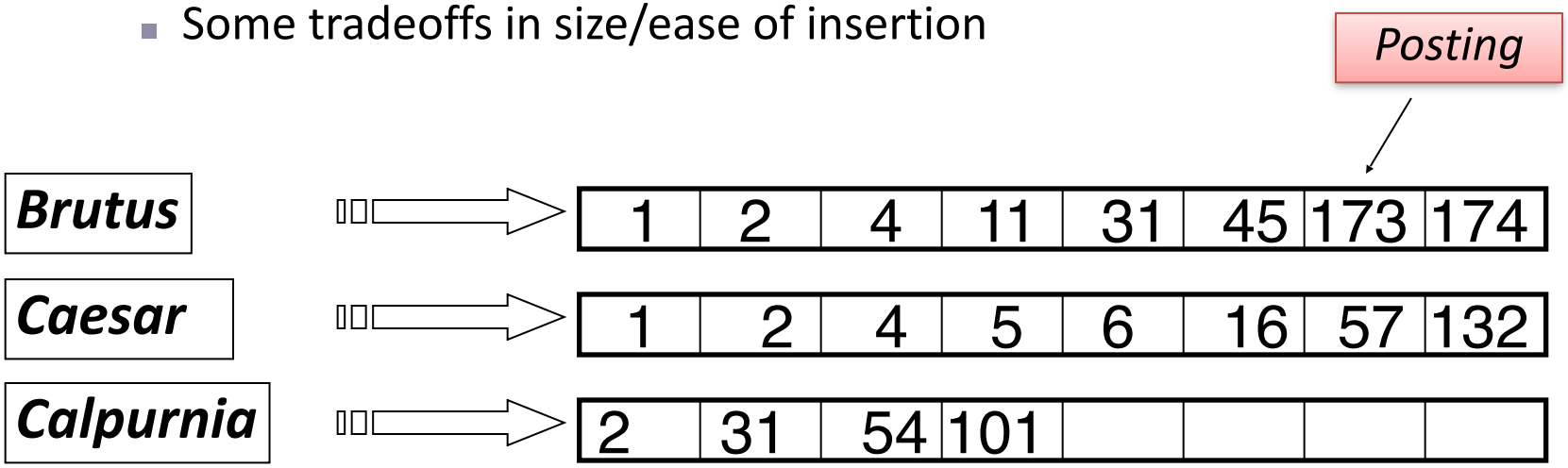

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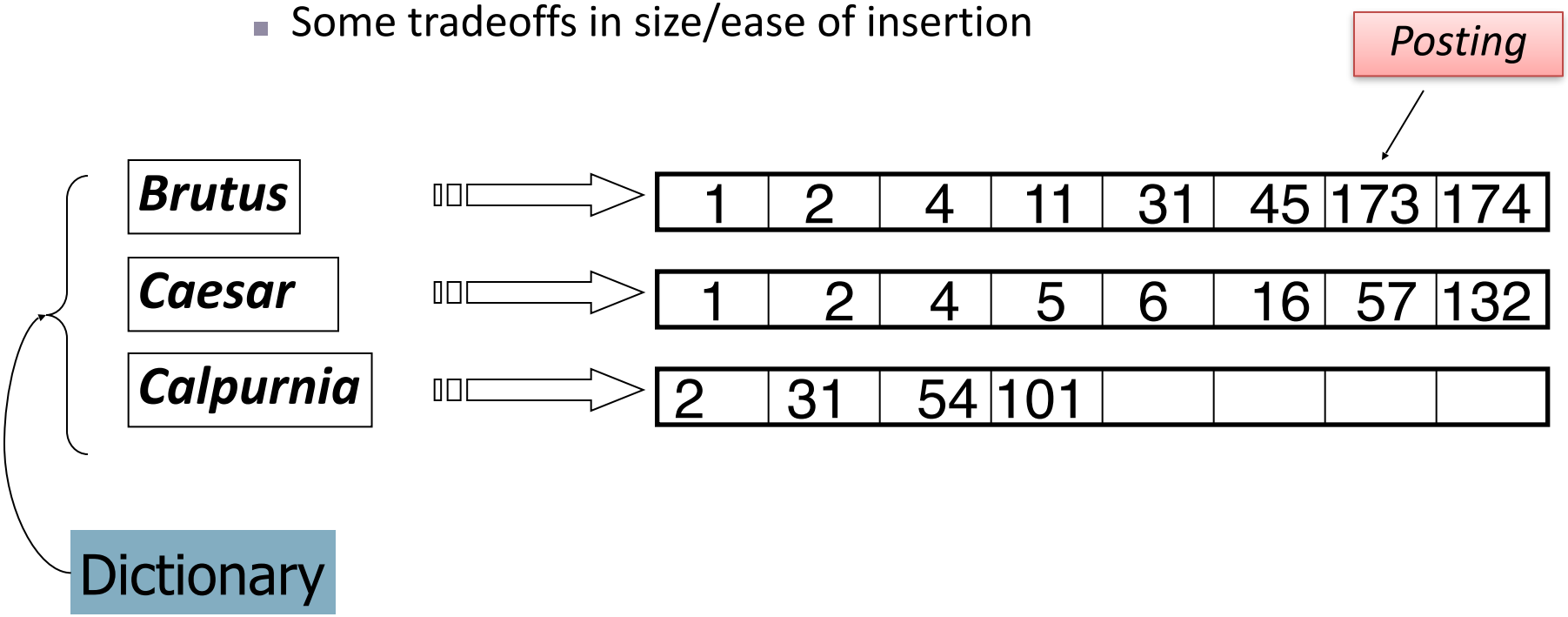

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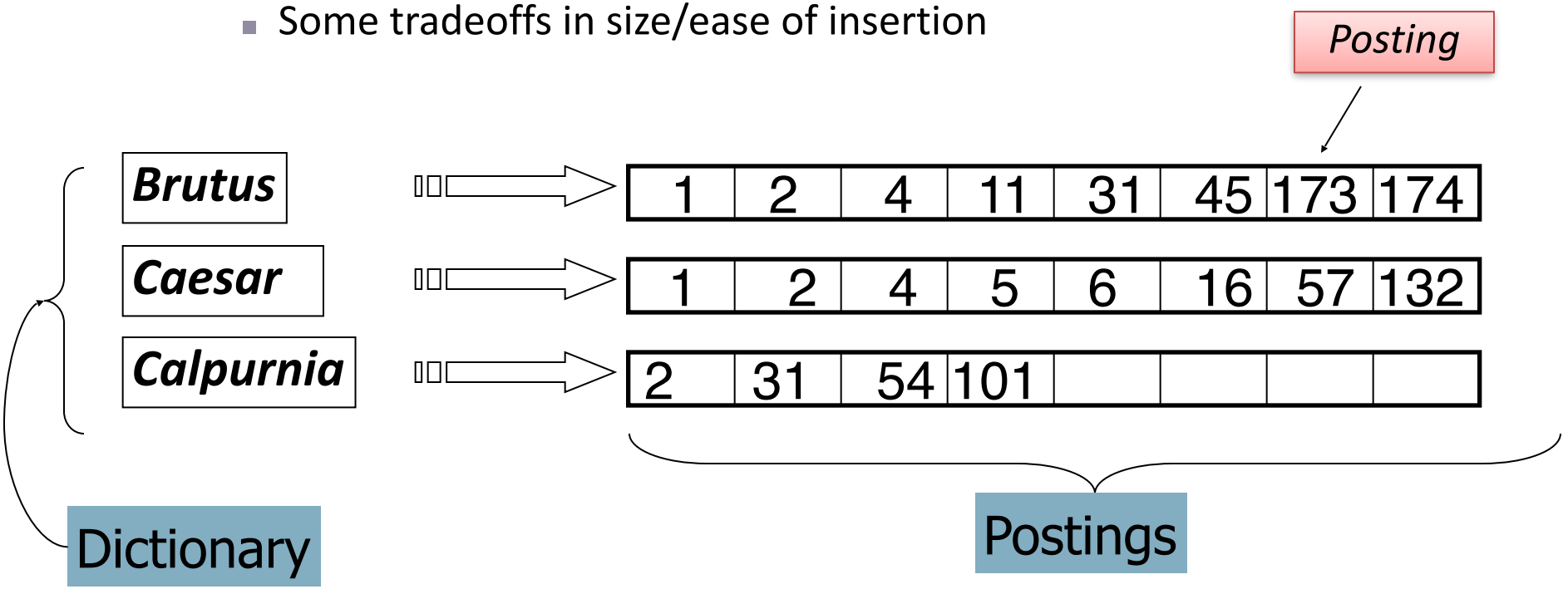

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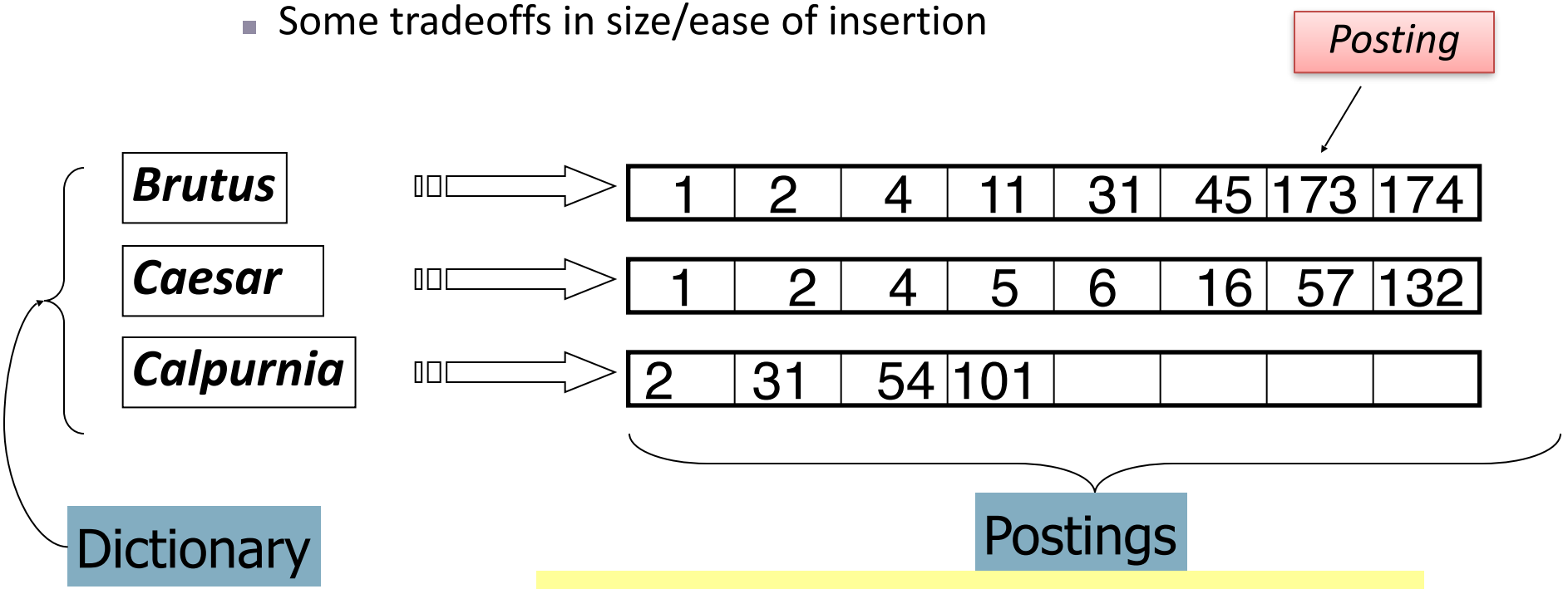
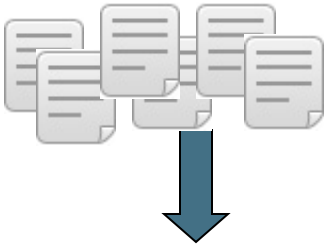


Sorted by docID (more later on why).

Inverted index construction

Documents to be indexed



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⋮

Inverted index construction

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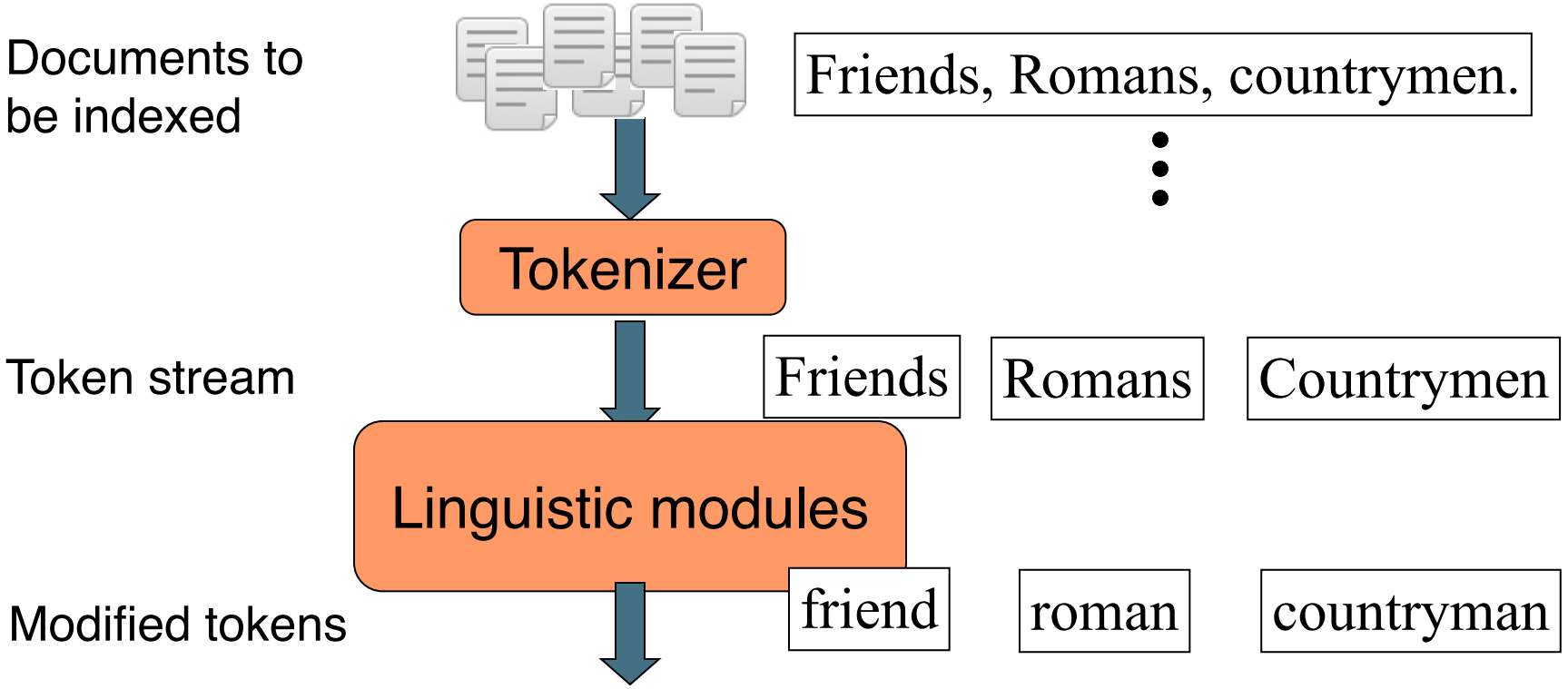
Friends, Romans, countrymen.

Tokenizer

Token stream

Friends | Romans | Countrymen

Inverted index construction



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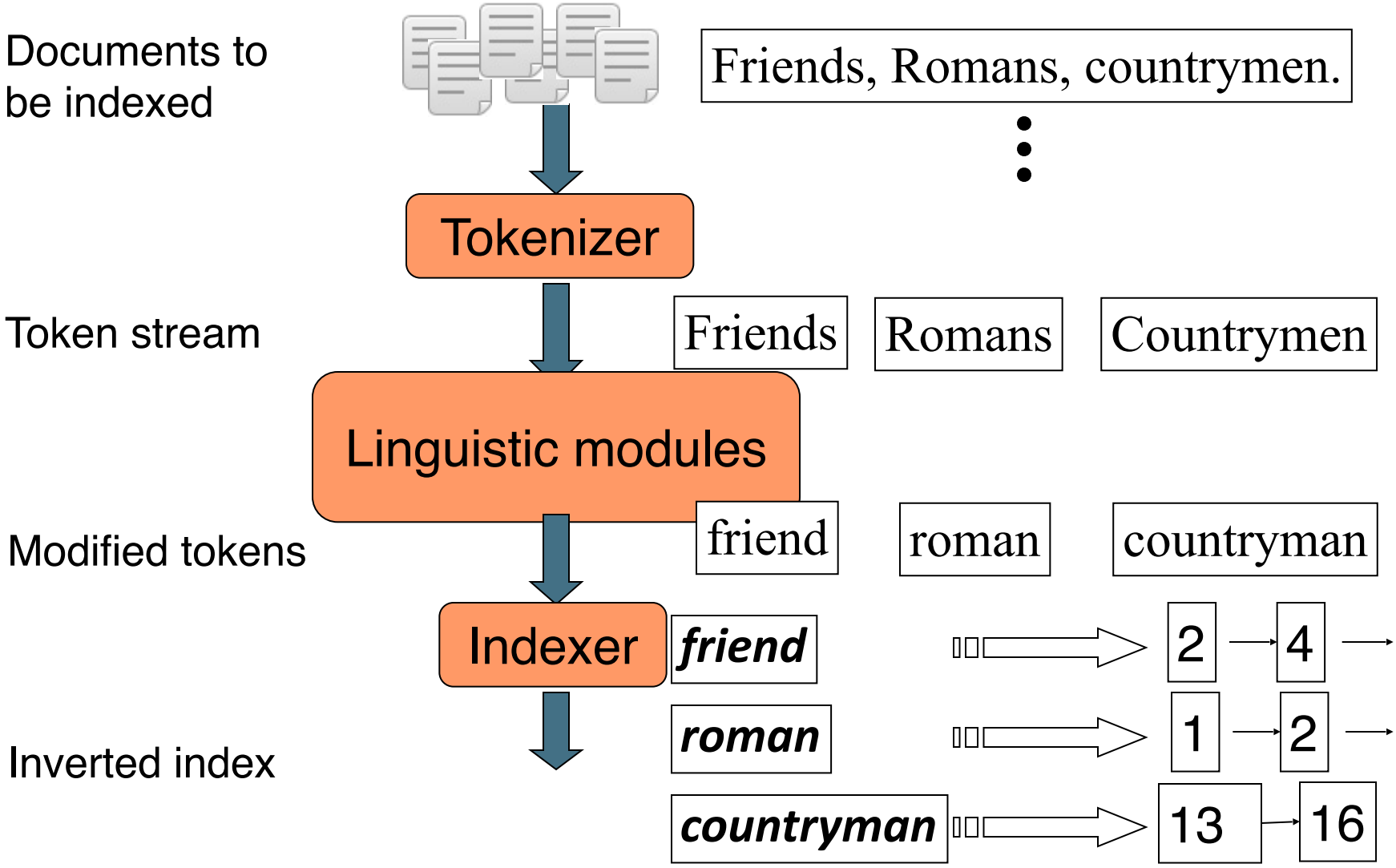

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  - We may wish different forms of a root to match
    - ***authorize***, ***authorization***
- Stop words
  - We may omit very common words (or not)
    - ***the, a, to, of***

Indexer steps: Token sequence

- Sequence of (Modified token, Document ID) pairs.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Indexer steps: Sort

- Sort by terms
  - At least conceptually
    - And then docID

Core indexing step

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
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me	1
so	2
let	2
it	2
be	2
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the	2
noble	2
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hath	2
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ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Indexer steps: Dictionary & Postings

- Multiple term entries in a single document are merged.
- Split into Dictionary and Postings
- Doc. frequency information is added.

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
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let	2
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was	2
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term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

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be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
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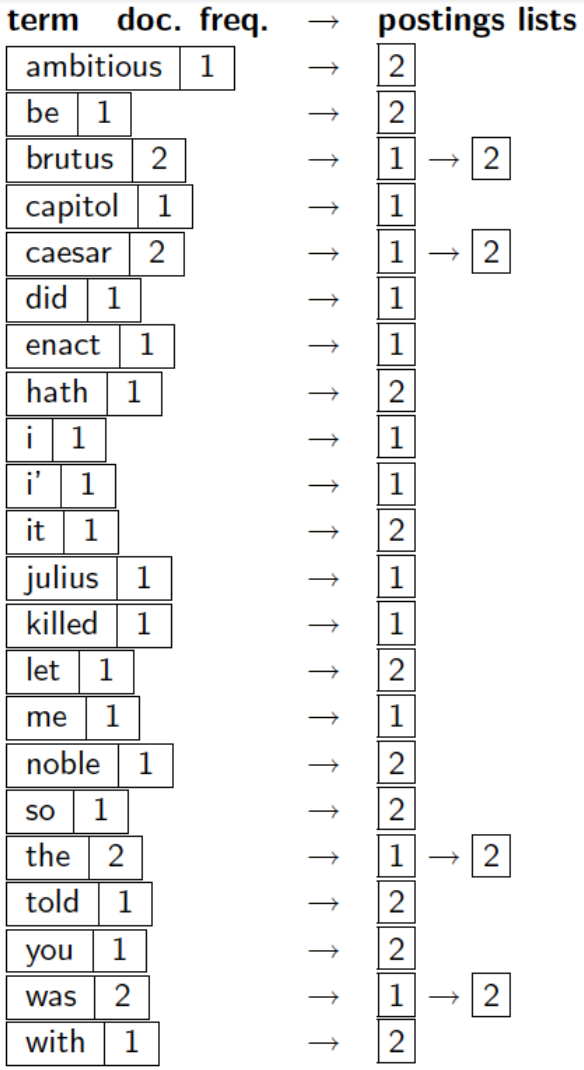
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Why frequency?
Will discuss later.

Where do we pay in storage?



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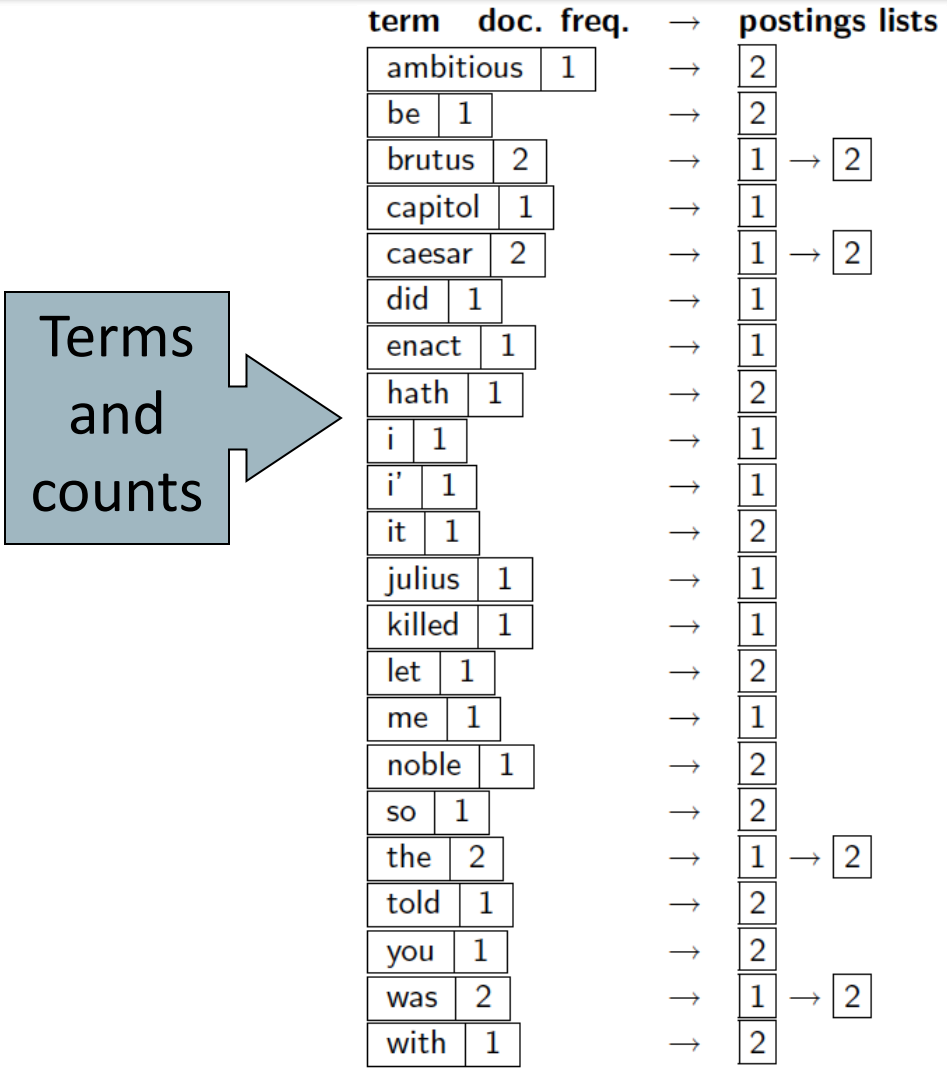

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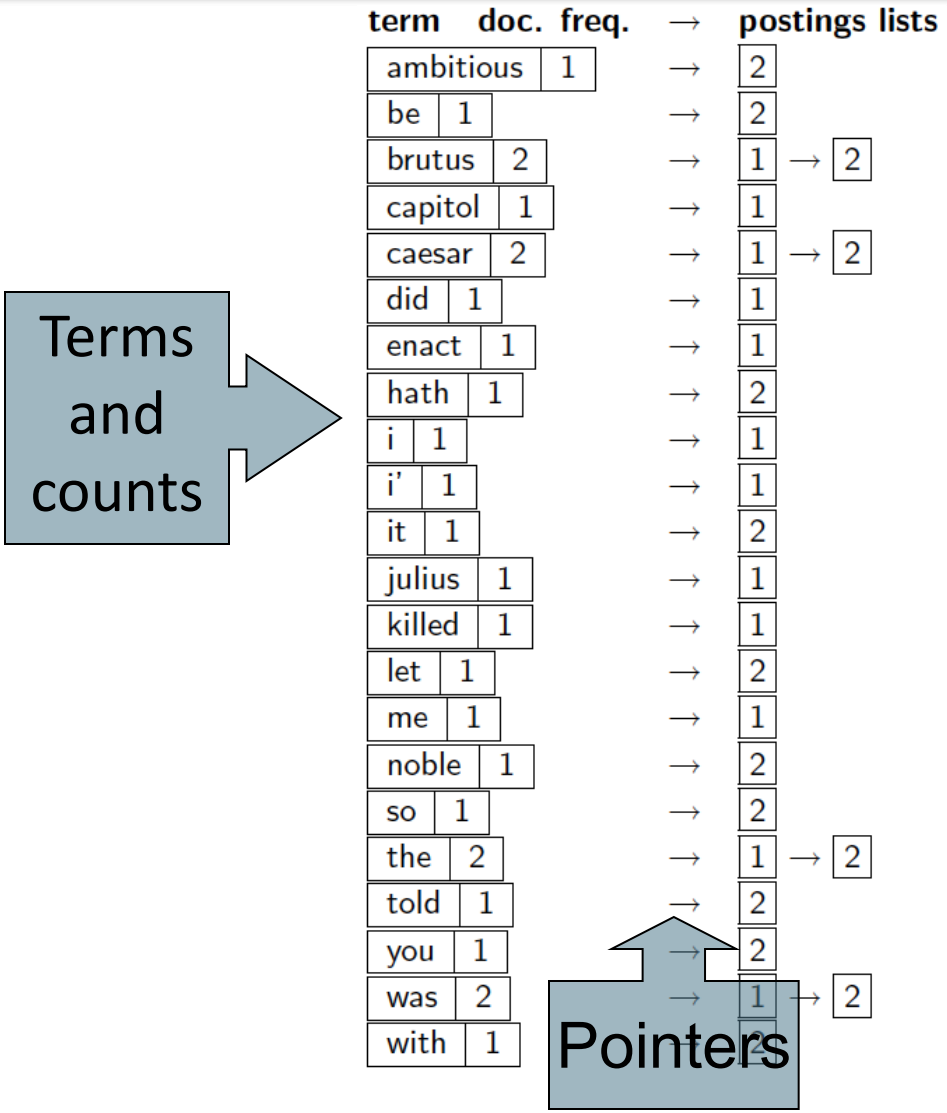

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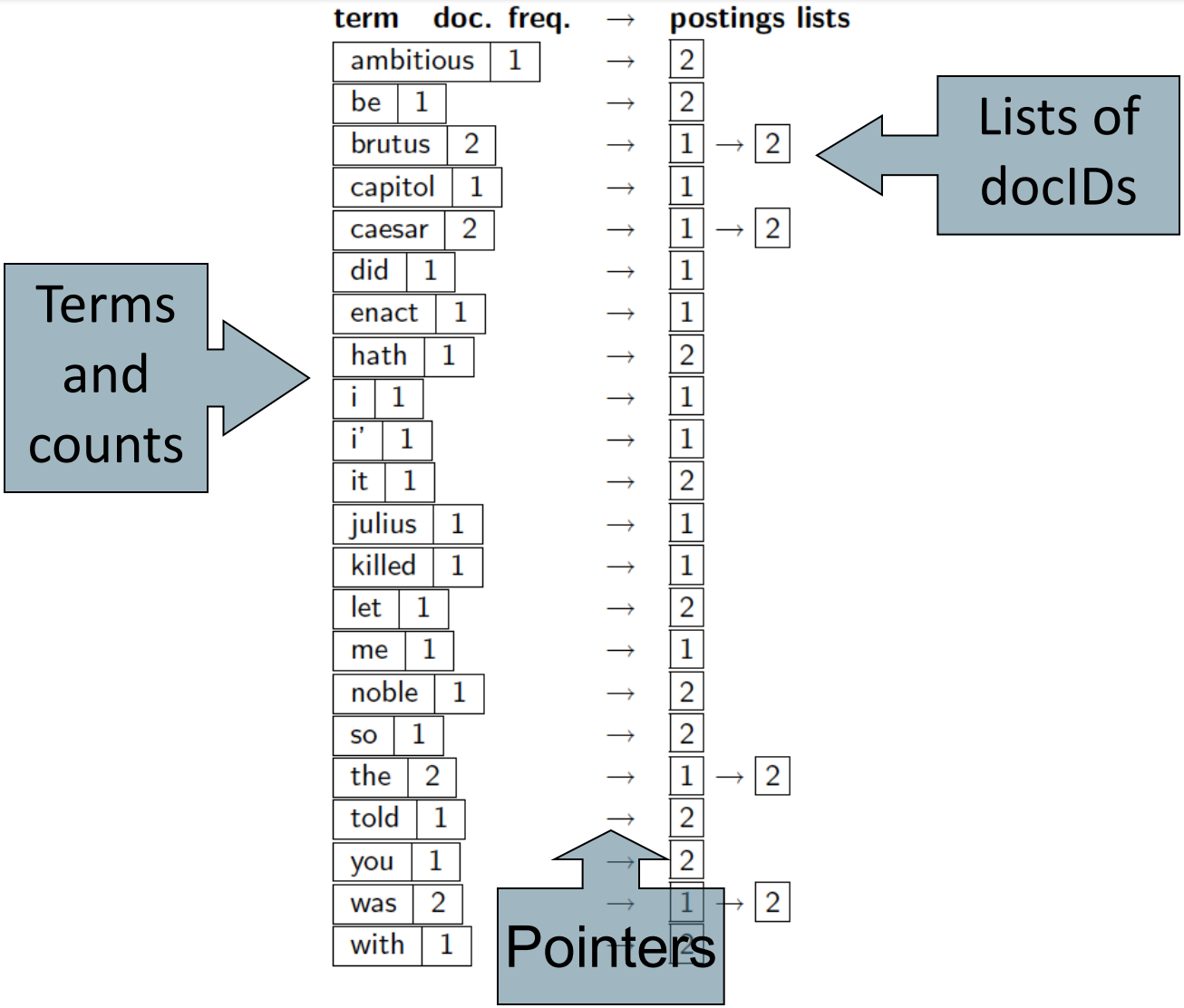

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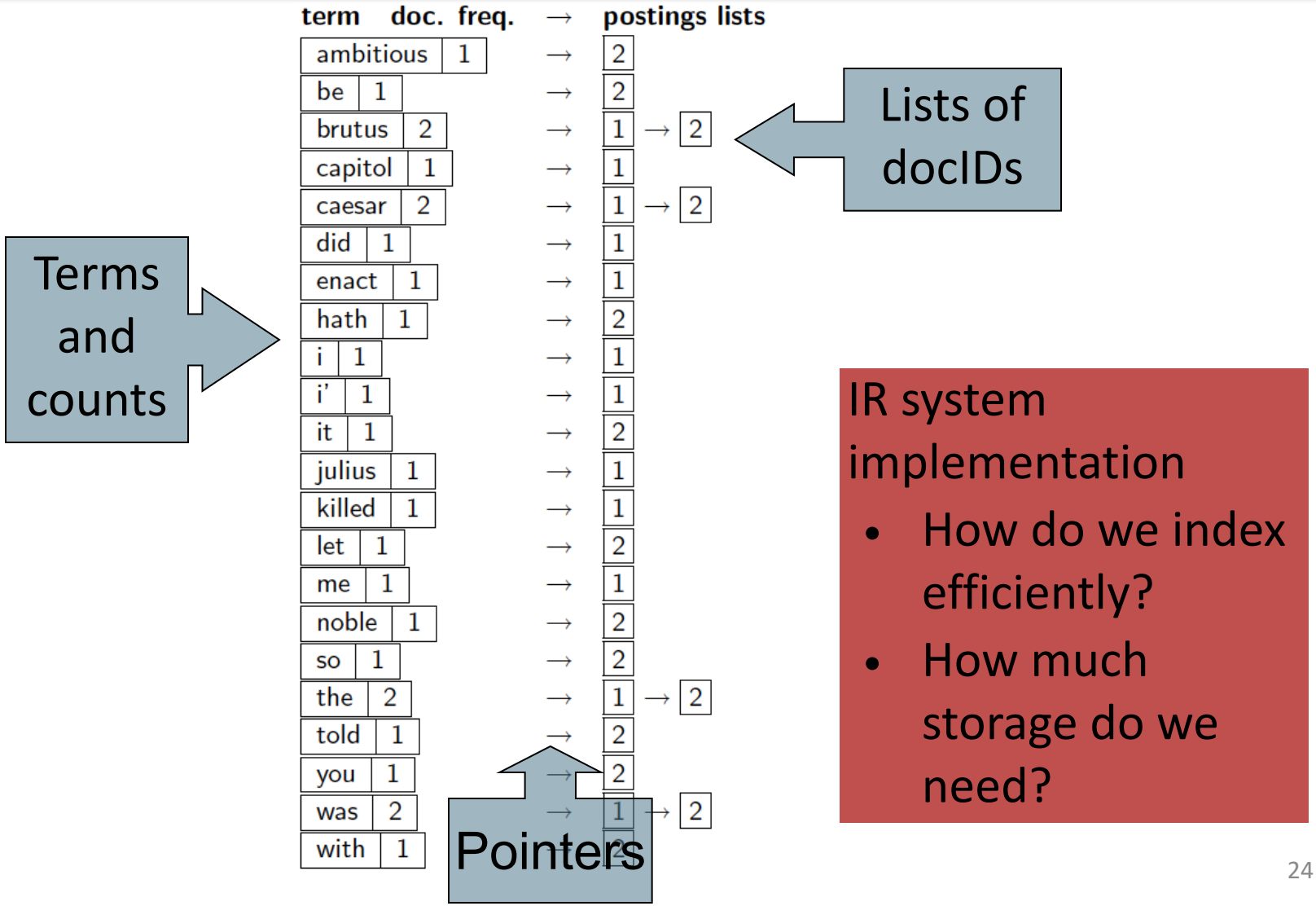

Query processing with an inverted index

The index we just built

- How do we process a query?
  - Later – what kinds of queries can we process?

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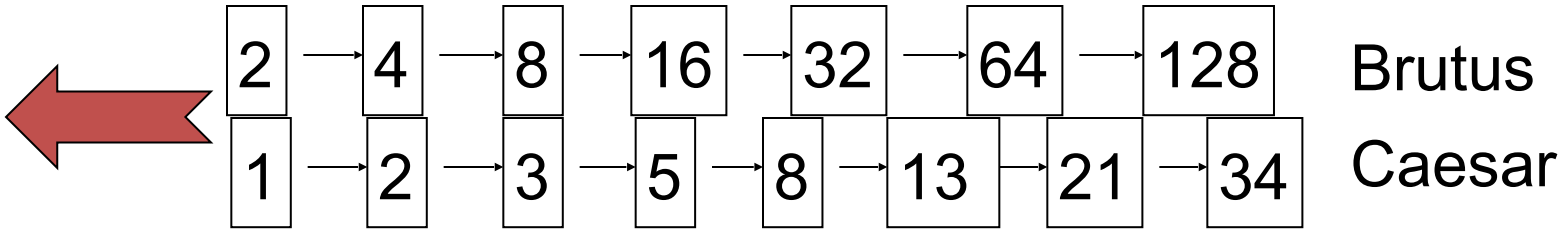
Query processing: AND

- Consider processing the query:

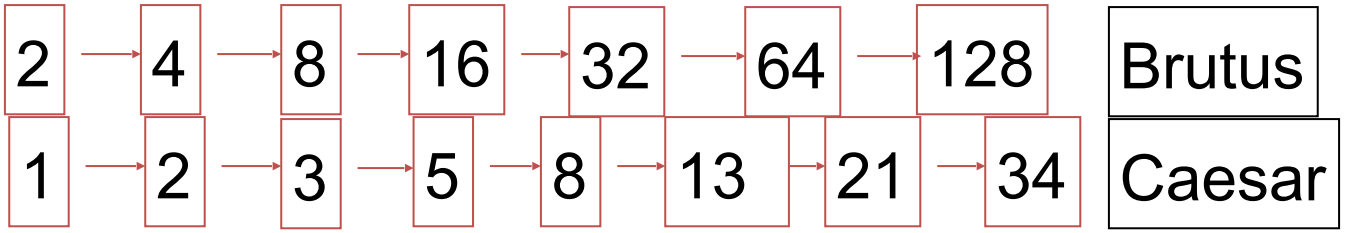
  Brutus *AND* ***Caesar***

  - Locate ***Brutus*** in the Dictionary;
    - Retrieve its postings.
  - Locate ***Caesar*** in the Dictionary;
    - Retrieve its postings.
  - "Merge" the two postings (intersect the document sets):



The merge

- Walk through the two postings simultaneously, in time linear in the total number of postings entries



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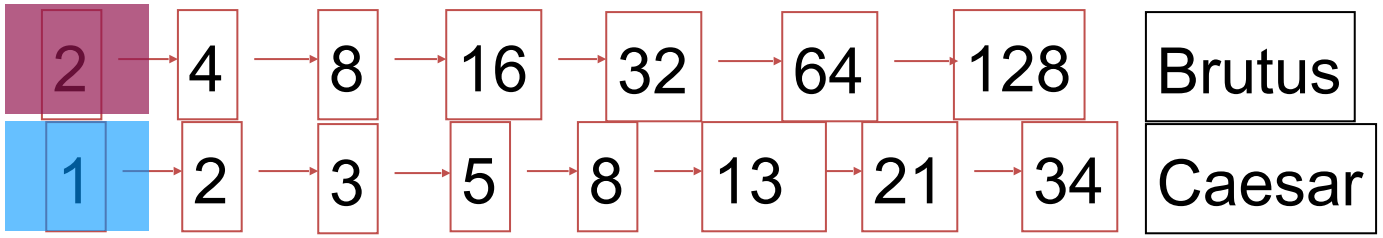

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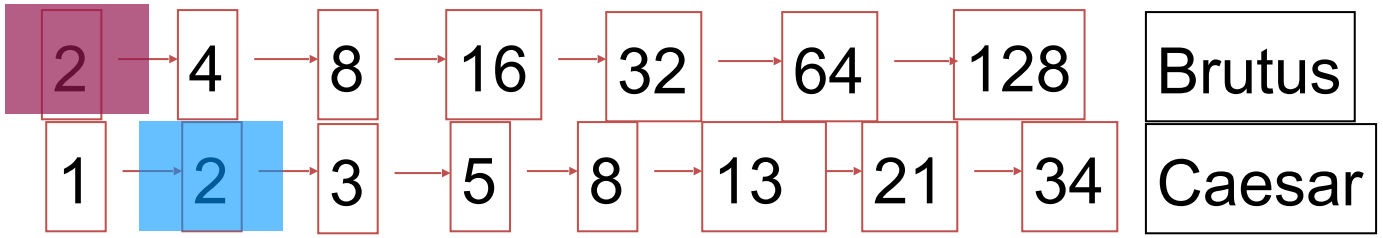

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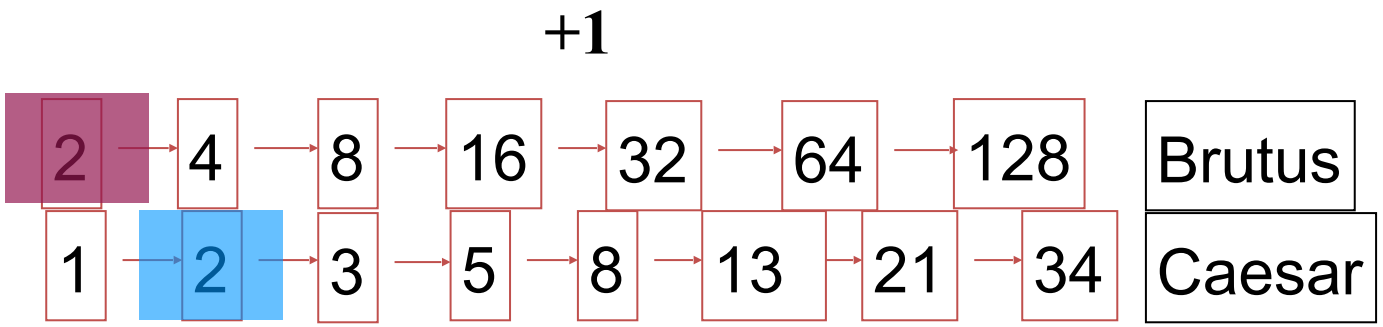

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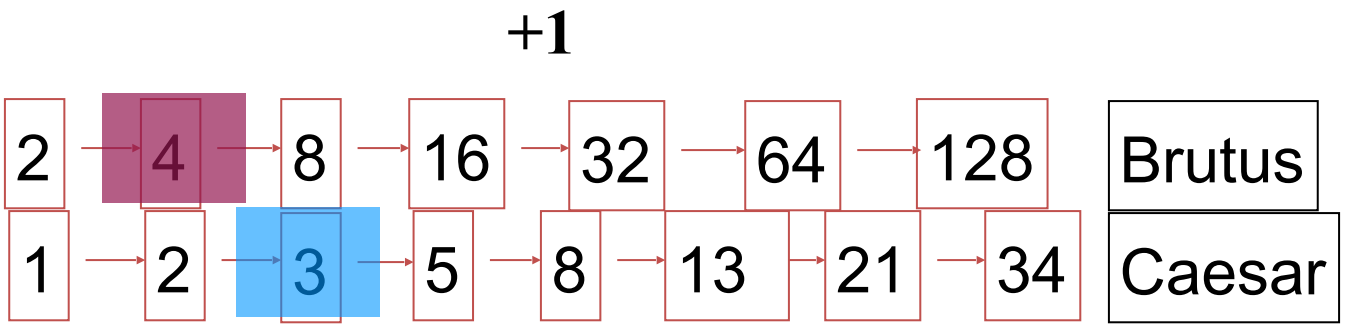

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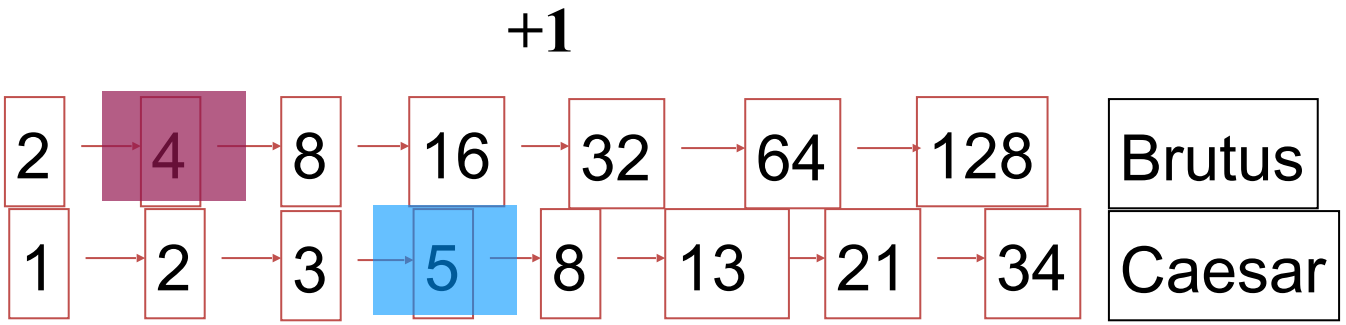

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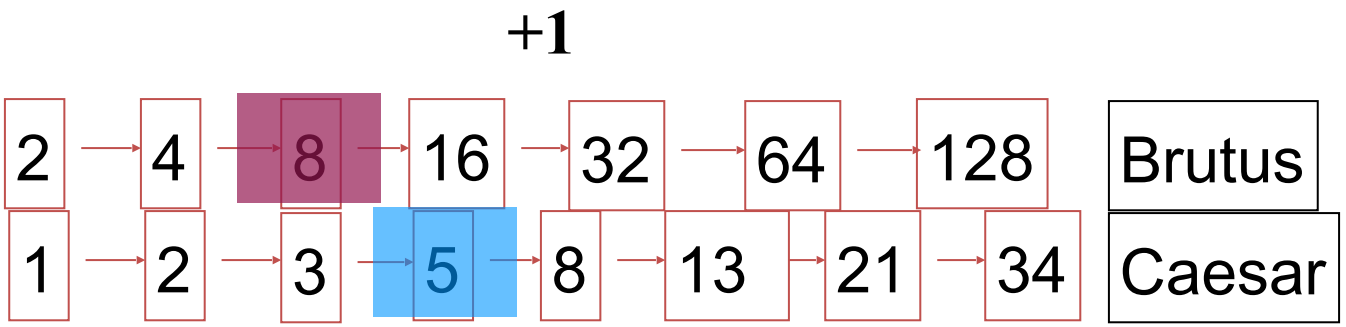

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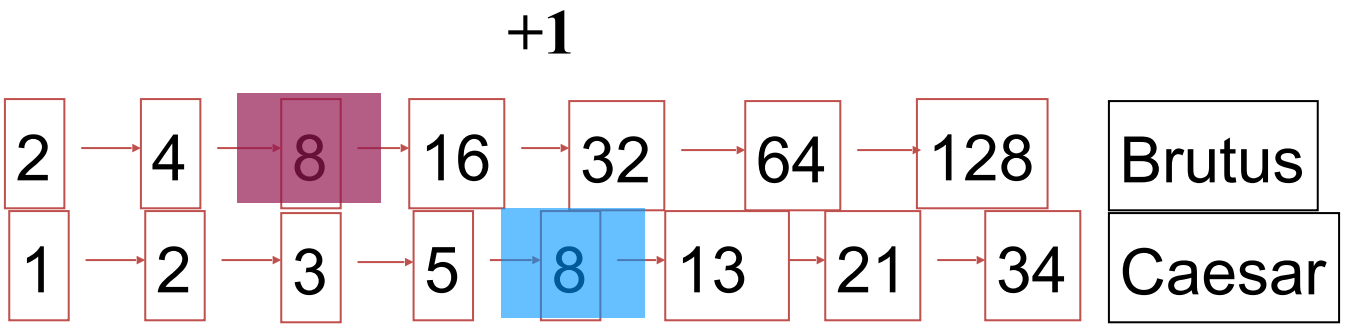

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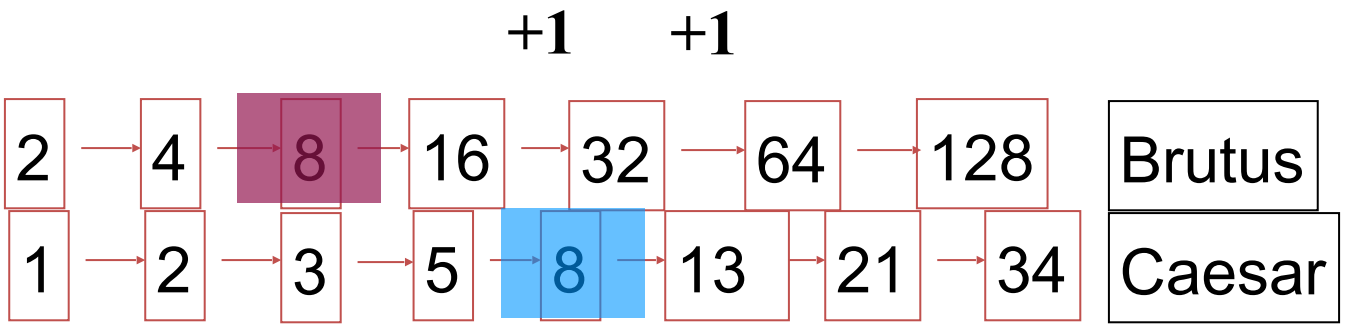

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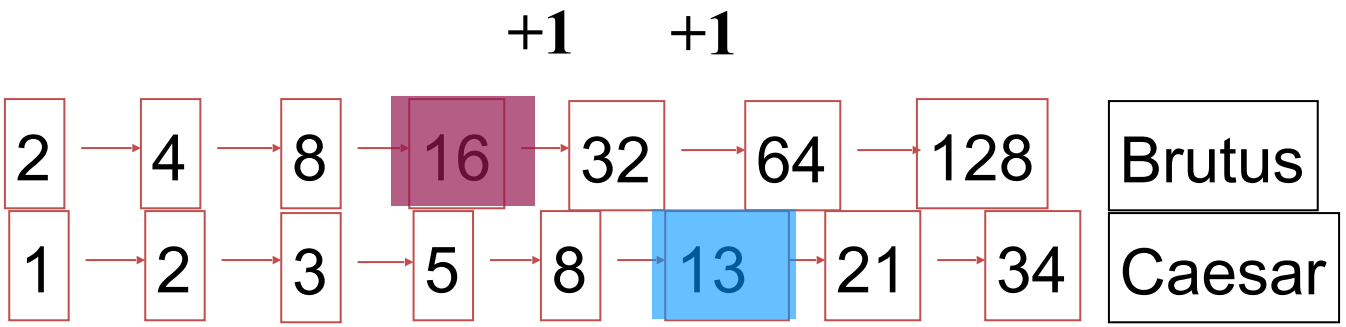

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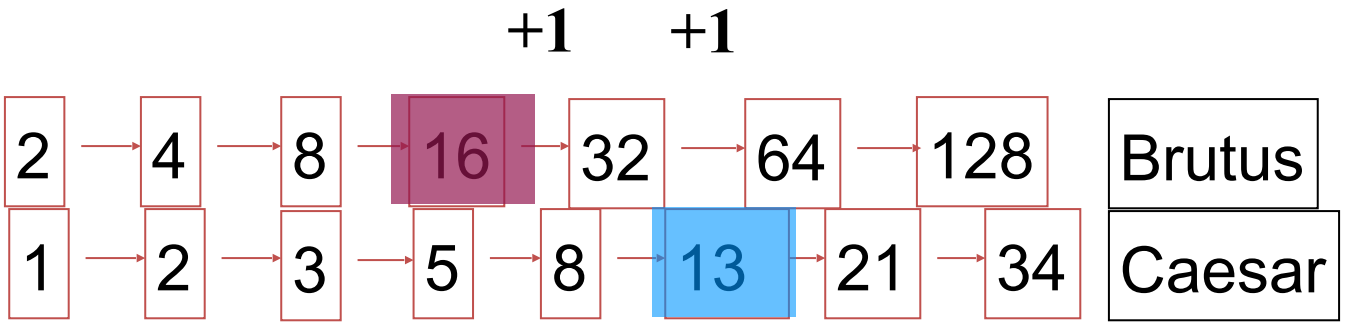

If the list lengths are *x* and *y*, the merge takes O(*x*+*y*) operations.

Crucial: postings sorted by docID.

Intersecting two postings lists (a "merge" algorithm)

```
INTERSECT(p1, p2)
 1  answer ← ⟨ ⟩
 2  while p1 ≠ NIL and p2 ≠ NIL
 3  do if docID(p1) = docID(p2)
 4        then ADD(answer, docID(p1))
 5             p1 ← next(p1)
 6             p2 ← next(p2)
 7        else if docID(p1) < docID(p2)
 8                then p1 ← next(p1)
 9                else p2 ← next(p2)
10  return answer
```

Boolean Queries

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- The Boolean retrieval model is being able to ask a query that is a Boolean expression:
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- Primary commercial retrieval tool for 3 decades.
- Many search systems you still use are Boolean:
  - Email, library catalog, macOS Spotlight

Example: WestLaw http://www.westlaw.com/

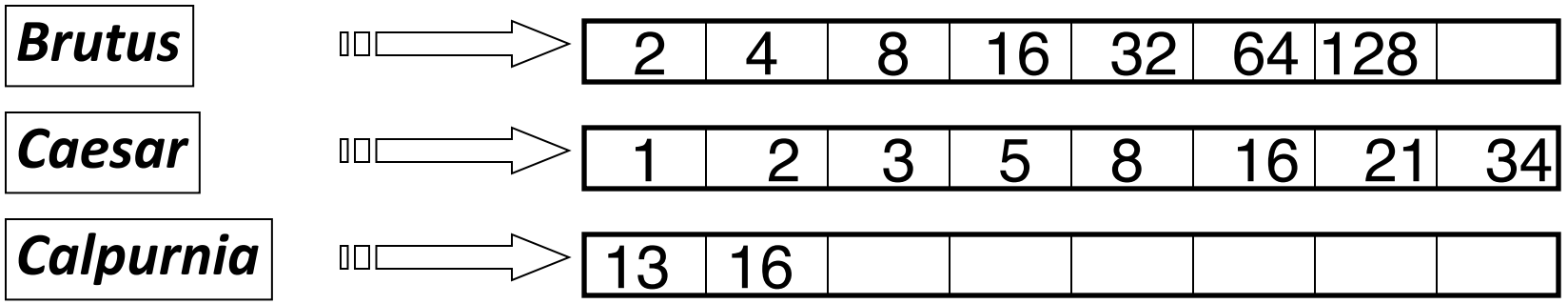
- Largest commercial (paying subscribers) legal search service (started 1975; ranking added 1992; new federated search added 2010)
- Tens of terabytes of data; ~700,000 users
- Majority of users *still* use boolean queries
- Example query:
  - What is the statute of limitations in cases involving the federal tort claims act?
  - LIMIT! /3 STATUTE ACTION /S FEDERAL /2 TORT / 3 CLAIM
    - /3 = within 3 words, /S = in same sentence

Example: WestLaw http://www.westlaw.com/

- Another example query:
  - Requirements for disabled people to be able to access a workplace
  - disabl! /p access! /s work-site work-place (employment /3 place
- Note that SPACE is disjunction, not conjunction!
- Long, precise queries; proximity operators; incrementally developed; not like web search
- Many professional searchers still like Boolean search
  - You know exactly what you are getting
- But that doesn't mean it actually works better….

Query optimization

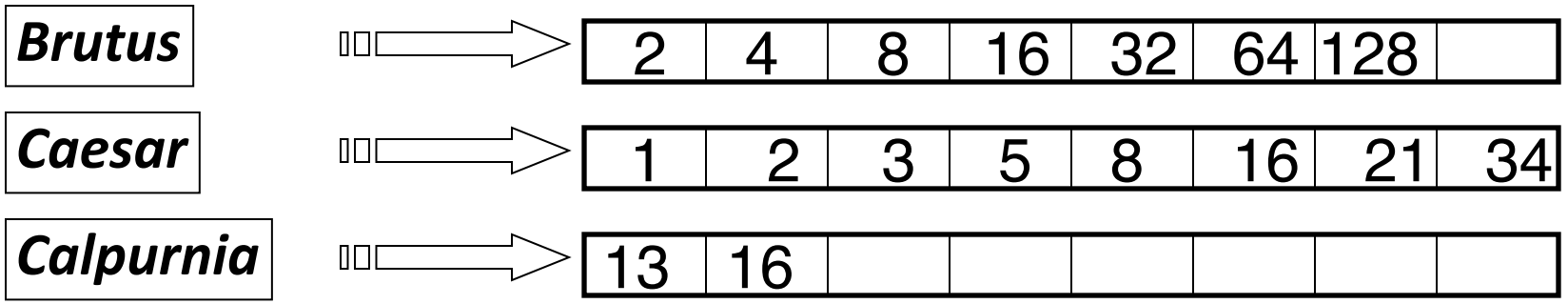
- What is the best order for query processing?
- Consider a query that is an *AND* of *n* terms.
- For each of the *n* terms, get its postings, then *AND* them together.



Query: ***Brutus*** *AND* ***Calpurnia*** *AND* ***Caesar***

Query optimization example

- Process in order of increasing freq:
  - *start with smallest set, then keep cutting further*.



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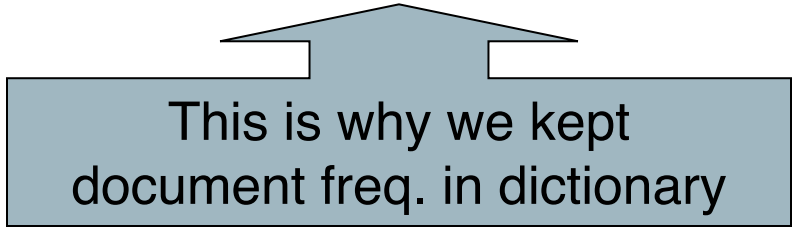

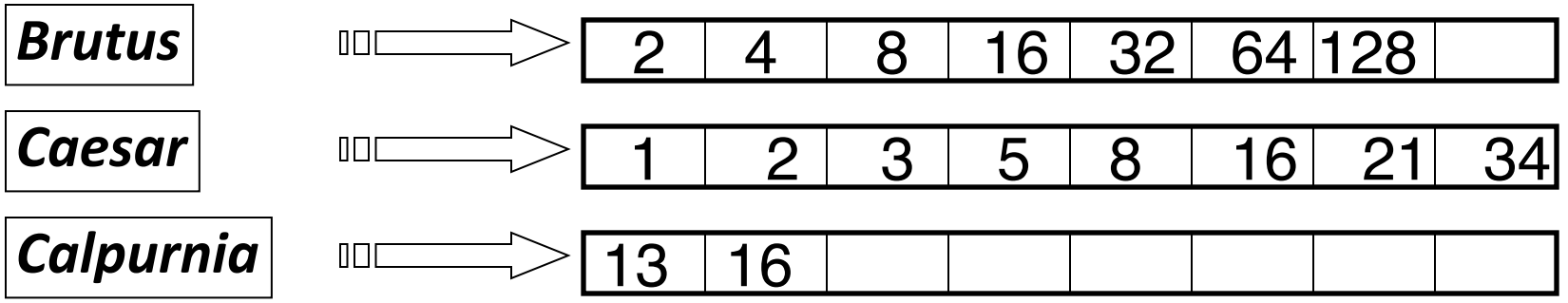

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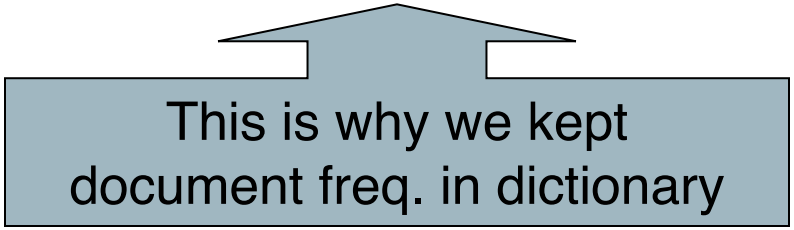

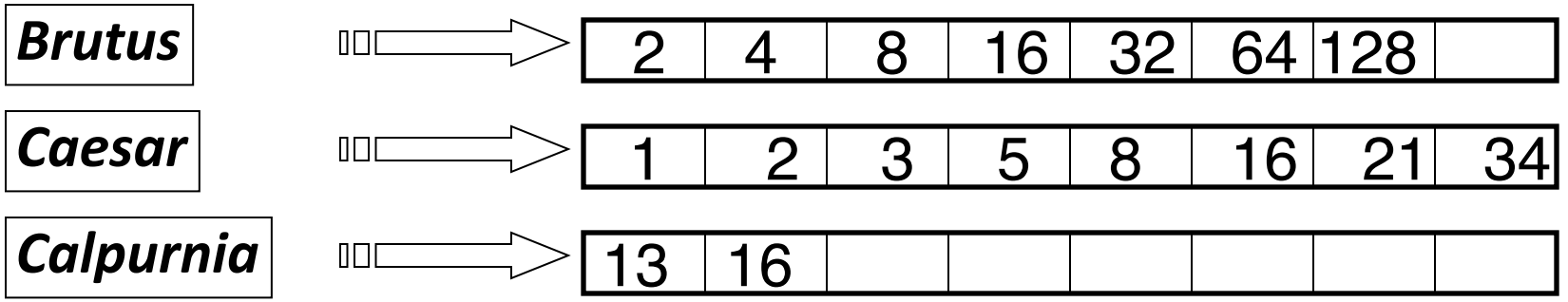

Execute the query as (***Calpurnia*** *AND* ***Brutus)*** *AND* ***Caesar***.

Phrase Queries and Positional Indexes

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<*term* : *docs*> entries

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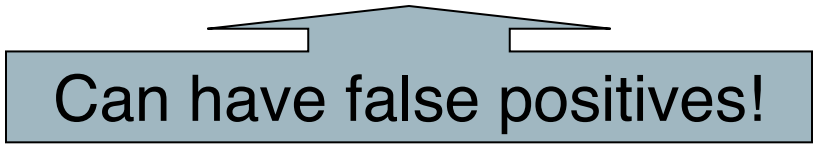
- Each of these biwords is now a dictionary term
- Two-word phrase query-processing is now immediate.

Longer phrase queries

- Longer phrases can be processed by breaking them down
- ***stanford university palo alto*** can be broken into the Boolean query on biwords:

stanford university *AND* ***university palo*** *AND* ***palo alto***

Without the docs, we cannot verify that the docs matching the above Boolean query do contain the phrase.



Issues for biword indexes

- False positives, as noted before
- Index blowup due to bigger dictionary
  - Infeasible for more than biwords, big even for them

- Biword indexes are not the standard solution (for all biwords) but can be part of a compound strategy

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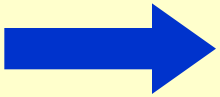
<***term***, number of docs containing ***term***;

doc1: position1, position2 … ;

doc2: position1, position2 … ;

etc.>

Doc	Text
1	Gold silver truck
2	Shipment of gold damaged in a fire
3	Delivery of silver arrived in a silver truck
4	Shipment of gold arrived in a truck



No.	Term	Times; Documents
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2	arrived	<2; 3,4>
3	damaged	<1; 2>
4	delivery	<1; 3>
5	fire	<1; 2>
6	gold	<3; 1,2,4>
7	of	<3; 2,3,4>
8	in	<3; 2,3,4>
9	shipment	<2; 2,4>
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How to easily print the sentences which contain the words and highlight the words?

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5	fire	<1; (2;7)>
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Term Dictionary

Posting List

How to easily print the sentences which contain the words and highlight the words?

Why do we keep “times” (frequency)?

Outline:
Inverted File Index

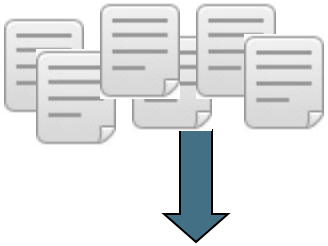
- Information retrieval
- Index construction & compression
- Ranked retrieval
- Performance measures
- Take-home messages

Index construction

- How do we construct an index?
- What strategies can we use with limited main memory?

Inverted index construction

Documents to be indexed



Friends, Romans, countrymen.

⋮

Inverted index construction

Documents to be indexed

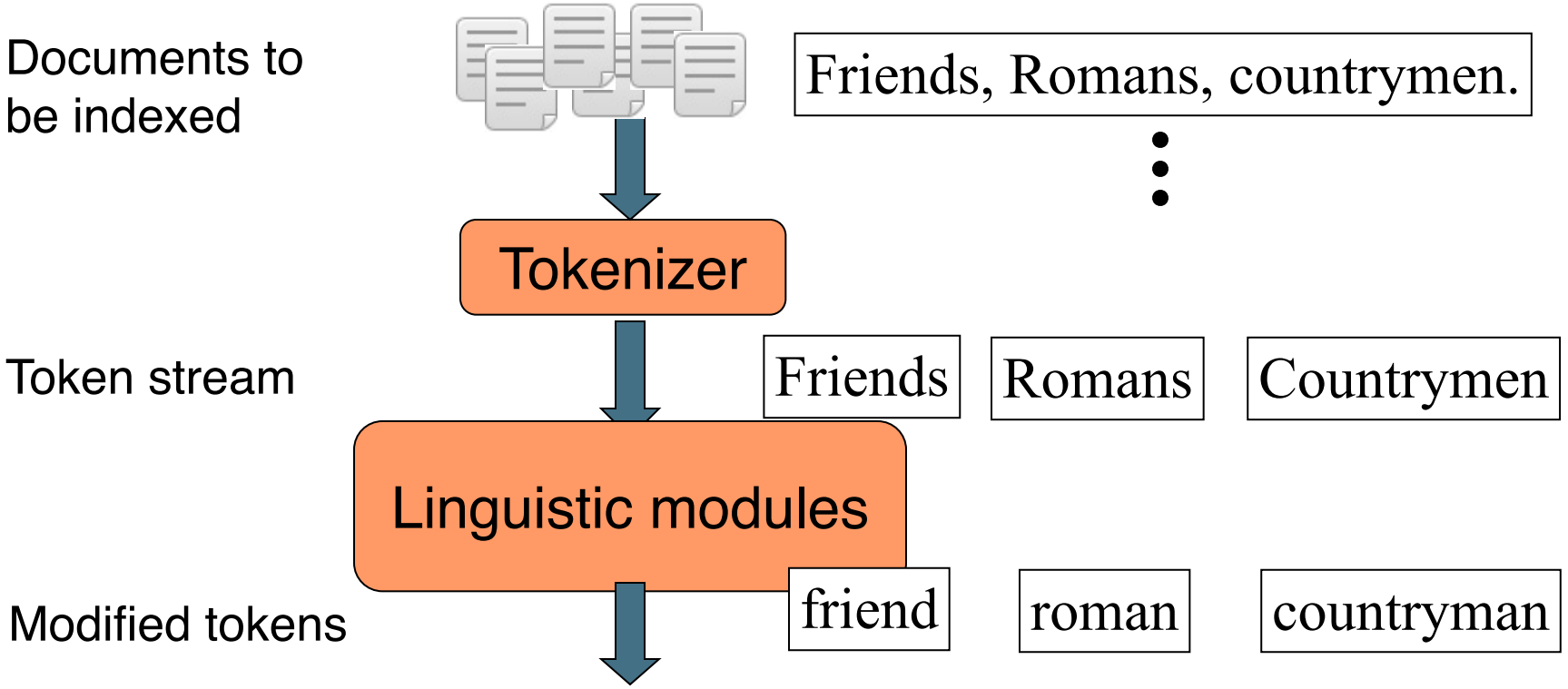
Friends, Romans, countrymen.

Tokenizer

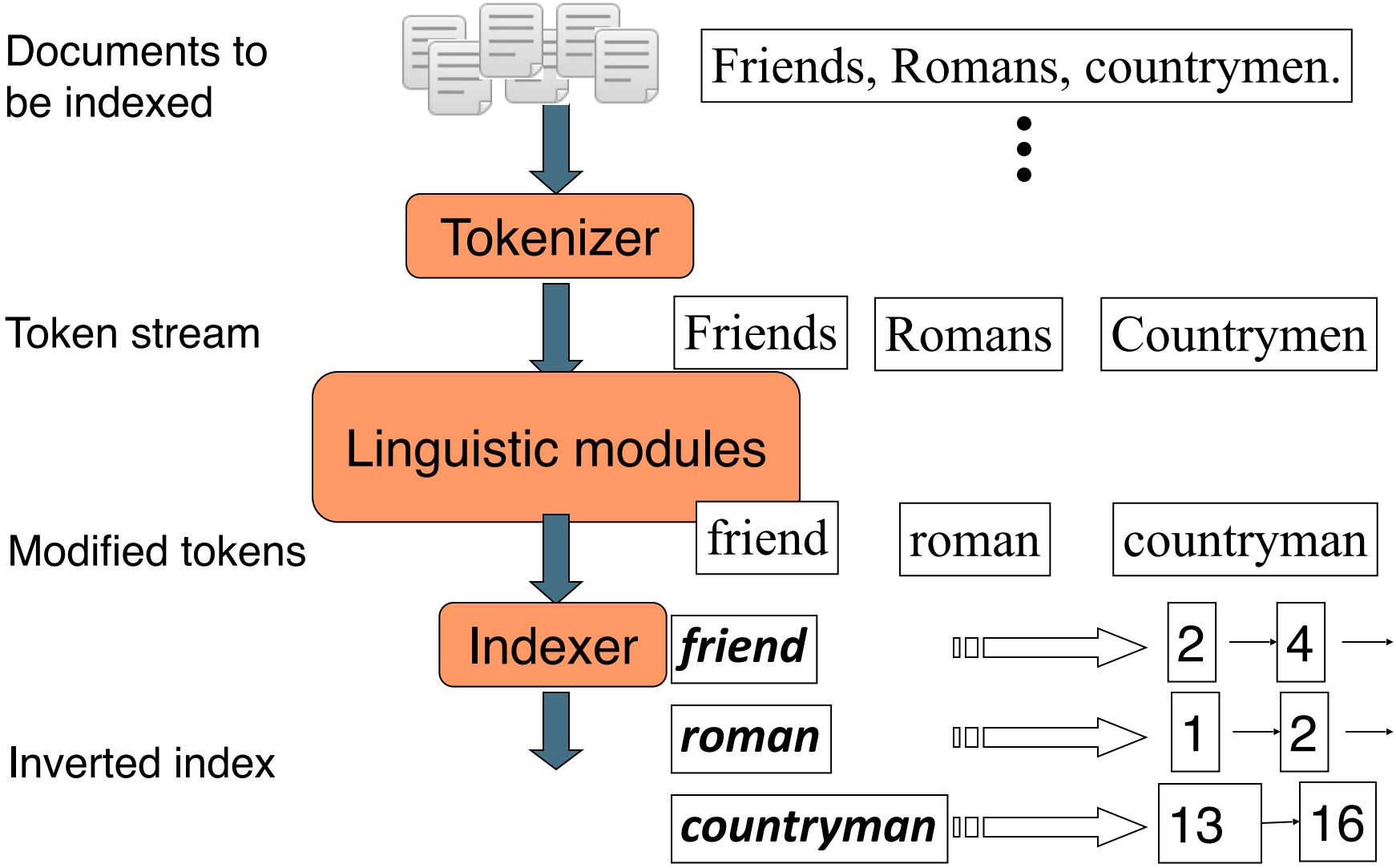
Token stream

Friends | Romans | Countrymen

Inverted index construction



Inverted index construction



Recall index construction

- Documents are parsed to extract words and these are saved with the Document ID.

Doc 1

I did enact Julius Caesar I was killed i' the Capitol; Brutus killed me.

Doc 2

So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Key step

- After all documents have been parsed, the inverted file is sorted by terms.

We focus on this sort step.

Term	Doc #
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Term	Doc #
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Sort-based index construction

- As we build the index, we parse docs one at a time.
  - The final postings for any term are incomplete until the end.
- At 8 bytes per *(termID, docID)*, demands a lot of space for large collections.
- T = 100,000,000 in the case of RCV1
  - So … we can do this in memory today, but typical collections are much larger. E.g., the *New York Times* provides an index of >150 years of newswire
- Thus: We need to store intermediate results on disk.

Sort using disk as “memory”?

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- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?

Sort using disk as "memory"?

- Can we use the same index construction algorithm for larger collections, but by using disk instead of memory?
- No: Sorting T = 100,000,000 records on disk is too slow – too many disk seeks.
- We need an *external* sorting algorithm.

External memory indexing

BSBI: Blocked sort-based Indexing (Sorting with fewer disk seeks)

- 8-byte records *(termID, docID)*
- These are generated as we parse docs
- Must now sort 100M such 8-byte records by *termID*
- Define a Block ~ 10M such records
  - Can easily fit a couple into memory
  - Will have 10 such blocks to start with
- Basic idea of algorithm:
  - Accumulate postings for each block, sort, write to disk
  - Then merge the blocks into one long sorted order

```
BSBIndexConstruction()
 1  n ← 0
 2  while (all documents have not been processed)
 3  do n ← n + 1
 4     block ← ParseNextBlock()
 5     BSBI-Invert(block)
 6     WriteBlockToDisk(block, f_n)
 7  MergeBlocks(f_1, ..., f_n; f_merged)
```

Sorting 10 blocks of 10M records

- First, read each block and sort within:
  - Quicksort takes O(*N* ln *N)* expected steps
  - In our case *N=10M*
- 10 times this estimate – gives us 10 sorted *runs* of 10M records each.
- Done straightforwardly, need 2 copies of data on disk
  - But can optimize this

Remaining problem with sort-based algorithm

- Our assumption was: we can keep the dictionary in memory.
- We need the dictionary (which grows dynamically) in order to implement a term to termID mapping.

SPIMI: Single-pass in-memory indexing

- Key idea 1: Generate separate dictionaries for each block – no need to maintain term-termID mapping across blocks.
- Key idea 2: Don’t sort. Accumulate postings in postings lists as they occur.
- With these two ideas we can generate a complete inverted index for each block.
- These separate indexes can then be merged into one big index.

SPIMI-Invert

```
SPIMI-INVERT(token_stream)
 1  output_file = NEWFILE()
 2  dictionary = NEWHASH()
 3  while (free memory available)
 4  do token ← next(token_stream)
 5     if term(token) ∉ dictionary
 6        then postings_list = ADDTODICTIONARY(dictionary, term(token))
 7        else postings_list = GETPOSTINGSLIST(dictionary, term(token))
 8     if full(postings_list)
 9        then postings_list = DOUBLEPOSTINGSLIST(dictionary, term(token))
10     ADDTOPOSTINGSLIST(postings_list, docID(token))
11  sorted_terms ← SORTTERMS(dictionary)
12  WRITEBLOCKTODISK(sorted_terms, dictionary, output_file)
13  return output_file
```

- Merging of blocks is analogous to BSBI.

SPIMI in action

Input token

Dictionary

SPIMI in action

Input token

Caesar d1

Dictionary

SPIMI in action

Input token

Caesar d1

Dictionary

caesar d1

SPIMI in action

Input token

Dictionary

Caesar d1

with d1

caesar d1

SPIMI in action

Input token

Caesar d1

with d1

Dictionary

with d1

caesar d1

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Dictionary

with d1

caesar d1

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Dictionary

brutus d1

with d1

caesar d1

SPIMI in action

Input token	Dictionary
Caesar d1	brutus d1
with d1	
Brutus d1	with d1
Caesar d2	
	caesar d1

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

Dictionary

brutus d1

with d1

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Dictionary

brutus d1

with d1

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Dictionary

brutus d1

with d1 d2

caesar d1 d2

SPIMI in action

Input token	Dictionary
Caesar d1	brutus d1
with d1	
Brutus d1	with d1 d2
Caesar d2	
with d2	
Brutus d3	caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

Dictionary

brutus d1 d3

with d1 d2

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Dictionary

brutus d1 d3

with d1 d2

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Dictionary

brutus d1 d3

with d1 d2 d3

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

Dictionary

brutus d1 d3

with d1 d2 d3

caesar d1 d2

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

Dictionary

brutus d1 d3

with d1 d2 d3

caesar d1 d2 d4

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

noble d5

Dictionary

brutus d1 d3

with d1 d2 d3

caesar d1 d2 d4

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

noble d5

Dictionary

brutus d1 d3

with d1 d2 d3

noble d5

caesar d1 d2 d4

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

noble d5

with d5

Dictionary

brutus d1 d3

with d1 d2 d3

noble d5

caesar d1 d2 d4

SPIMI in action

Input token

Caesar d1

with d1

Brutus d1

Caesar d2

with d2

Brutus d3

with d3

Caesar d4

noble d5

with d5

Dictionary

brutus d1 d3

with d1 d2 d3 d5

noble d5

caesar d1 d2 d4

SPIMI in action

Input token

Caesar d1
with d1
Brutus d1
Caesar d2
with d2
Brutus d3
with d3
Caesar d4
noble d5
with d5

Dictionary

brutus d1 d3

with d1 d2 d3 d5

noble d5

caesar d1 d2 d4

Sorted dictionary

brutus d1 d3

caesar d1 d2 d4

noble d5

with d1 d2 d3 d5

Inverted File Index

While not having enough memory ……

While not having enough memory ……

```
BlockCnt = 0;
while ( read a document D ) {
  while ( read a term T in D ) {
    if ( out of memory ) {
      Write BlockIndex[BlockCnt] to disk;
      BlockCnt ++;
      FreeMemory;
    }
    if ( Find( Dictionary, T ) == false )
      Insert( Dictionary, T );
    Get T's posting list;
    Insert a node to T's posting list;
  }
}
for ( i=0; i<BlockCnt; i++ )
  Merge( InvertedIndex, BlockIndex[i] );
```

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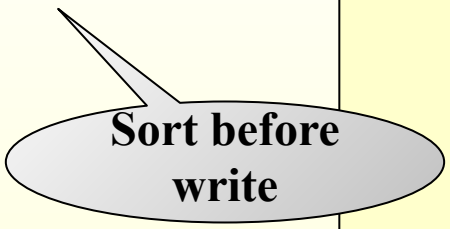

Distributed indexing

Distributed indexing (for web-scale indexing — don't try this at home!)

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—— Each node contains index of a subset of collection

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☞ **Solution 1: Term-partitioned index**

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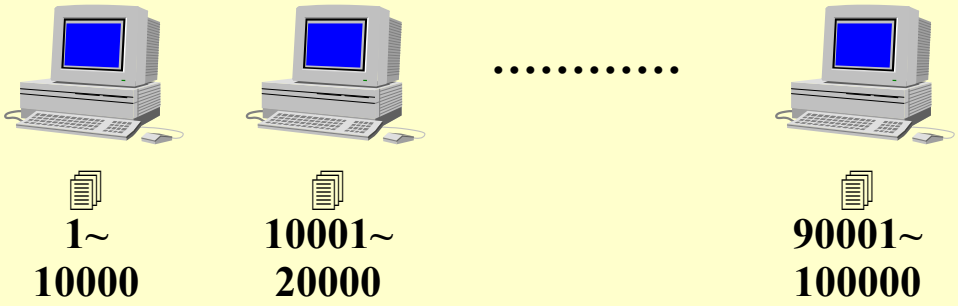


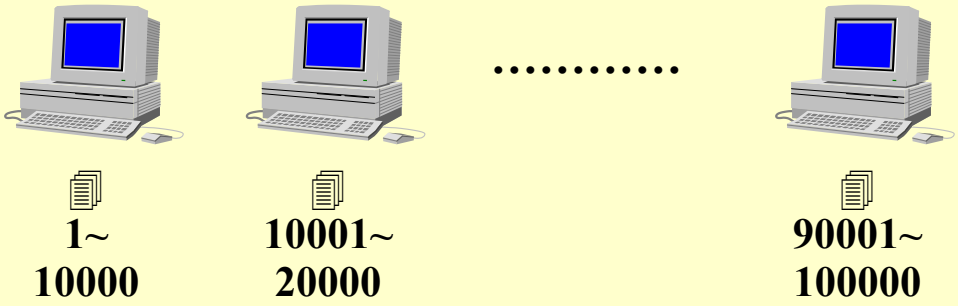
Distributed indexing (for web-scale indexing — don't try this at home!)

—— Each node contains index of a subset of collection

☞ **Solution 1: Term-partitioned index**

Which is better?

☞ **Solution 2: Document-partitioned index**



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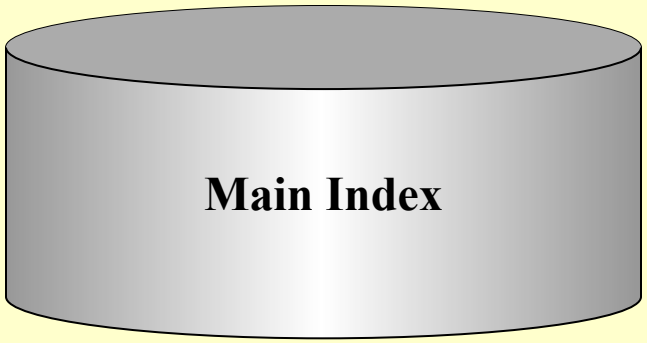

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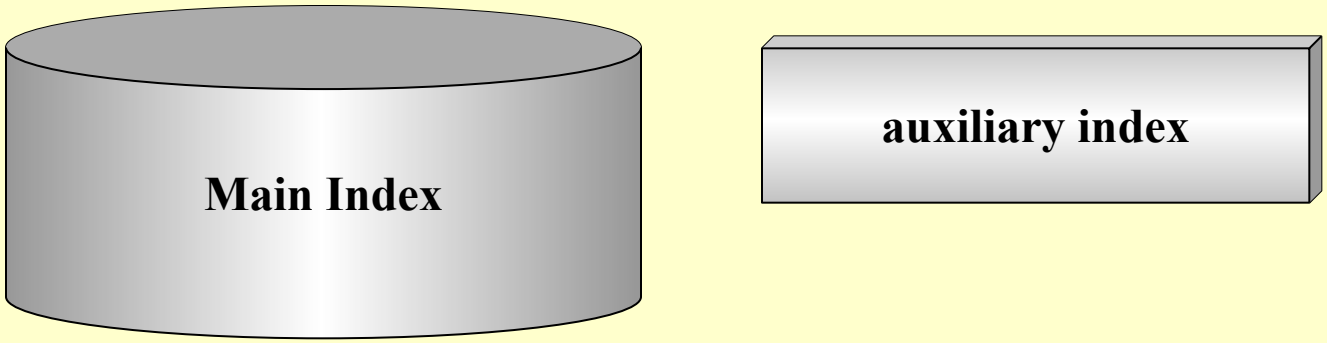

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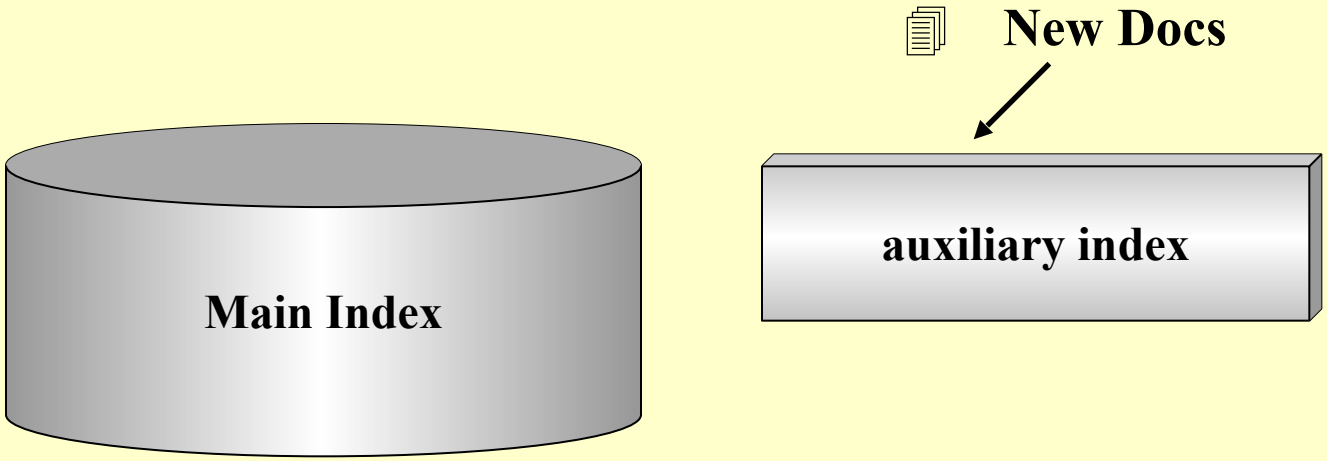

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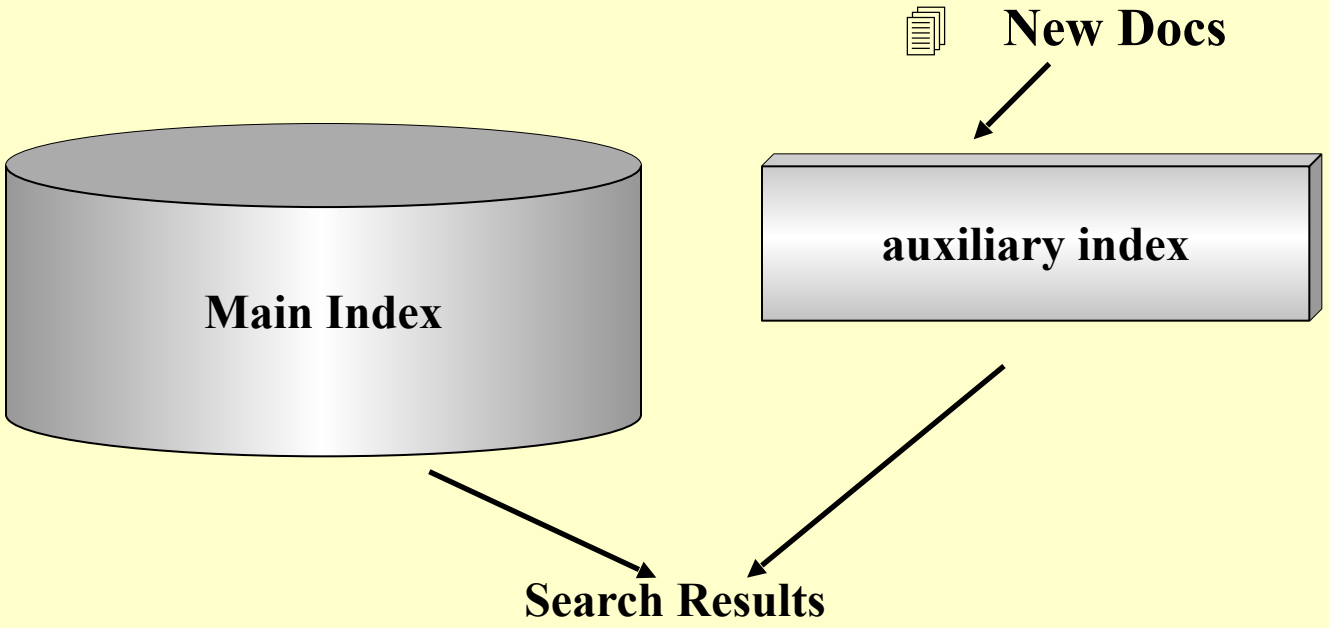

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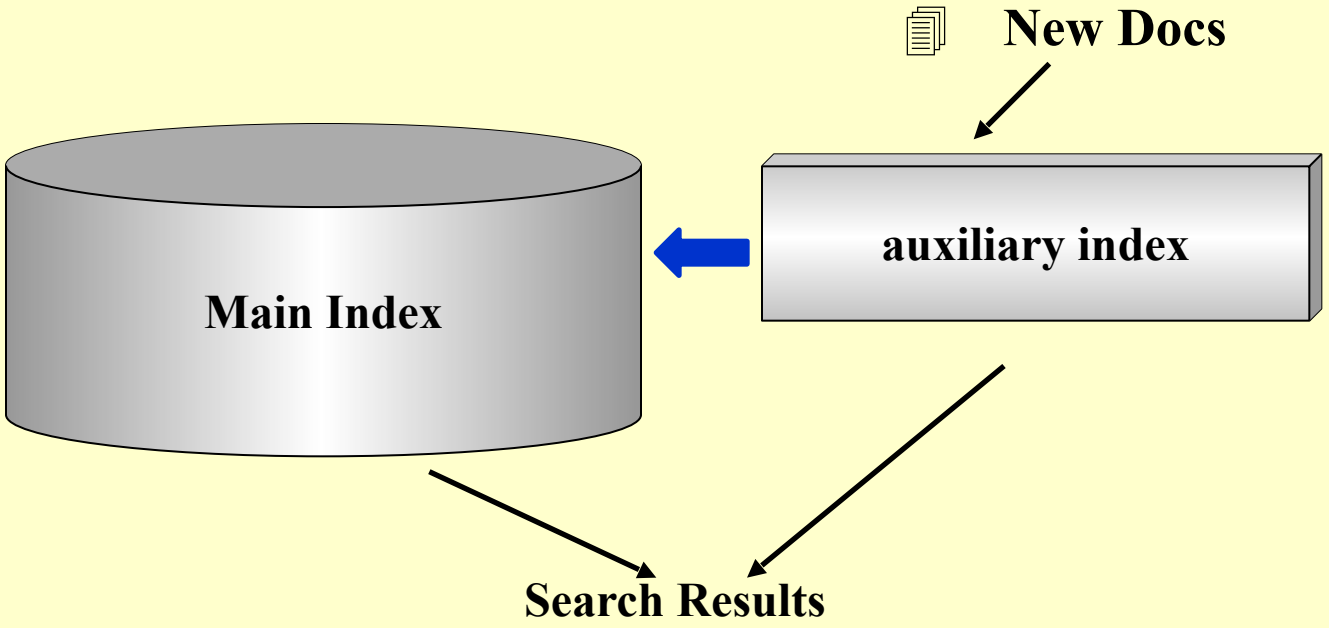

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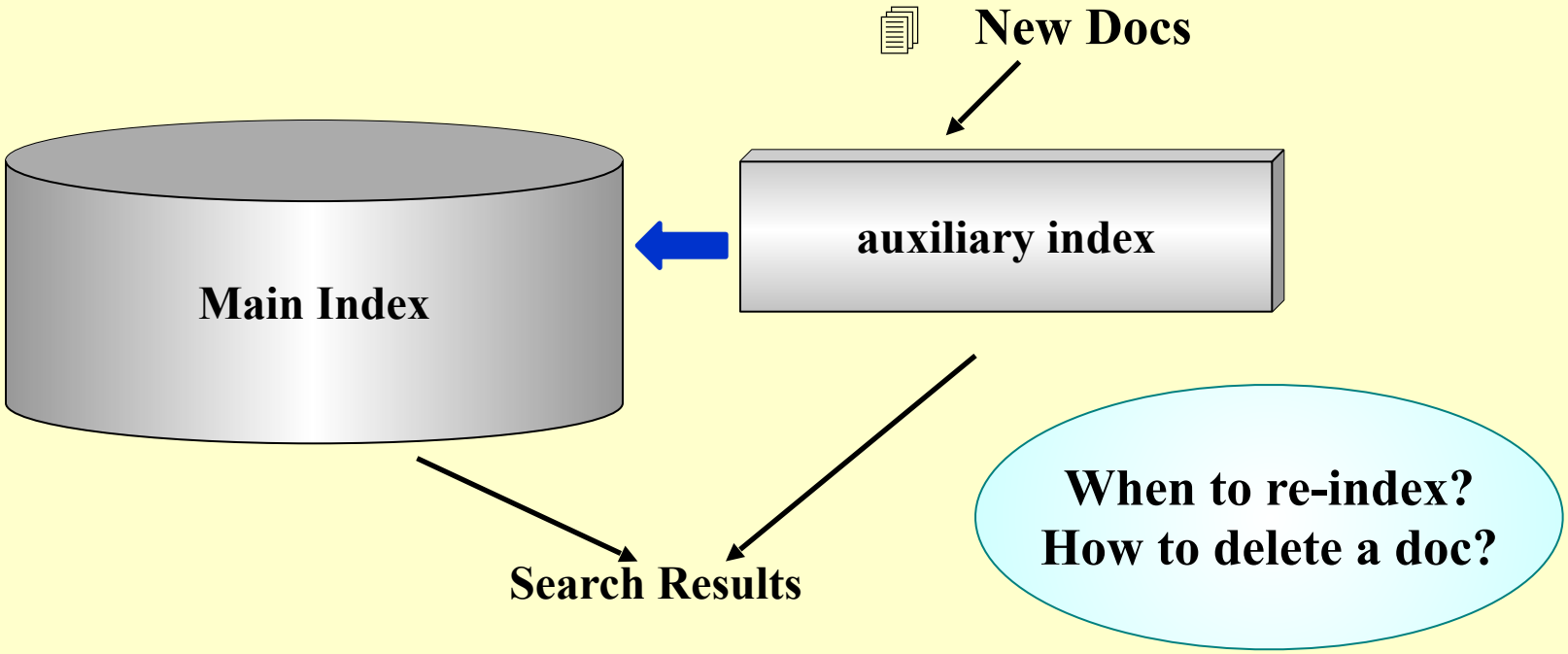

Simplest approach

- Maintain “big” main index
- New docs go into “small” auxiliary index
- Search across both, merge results
- Deletions
  - Invalidation bit-vector for deleted docs
  - Filter docs output on a search result by this invalidation bit-vector
- Periodically, re-index into one main index

Index Compression

Why compression (in general)?

- Use less disk space
  - Save a little money; give users more space
- Keep more stuff in memory
  - Increases speed
- Increase speed of data transfer from disk to memory
  - [read compressed data | decompress] is faster than [read uncompressed data]
- Premise: Decompression algorithms are fast
  - True of the decompression algorithms we use

Postings compression

- The postings file is much larger than the dictionary, factor of at least 10, often over 100 times larger
- Key desideratum: store each posting compactly.
- A posting for our purposes is a docID.
- For Reuters (800,000 documents), we would use 32 bits per docID when using 4-byte integers.
- Alternatively, we can use $\log_2 800{,}000 \approx 20$ bits per docID.
- Our goal: use far fewer than 20 bits per docID.

Postings: two conflicting forces

- A term like ***arachnocentric*** occurs in maybe one doc out of a million – we would like to store this posting using $\log_2$ 1M ≈ 20 bits.
- A term like ***the*** occurs in virtually every doc, so 20 bits/posting ≈ 2MB is too expensive.
  - Prefer 0/1 bitmap vector in this case (≈100K)

Gap encoding of postings file entries

- We store the list of docs containing a term in increasing order of docID.
  - ***computer***: 33,47,154,159,202 …
- Consequence: it suffices to store *gaps*.
  - 33,14,107,5,43 …
- Hope: most gaps can be encoded/stored with far fewer than 20 bits.
  - Especially for common words

Three postings entries

	encoding	postings list									
THE	docIDs	...		283042		283043		283044		283045	...
	gaps				1		1		1		...
COMPUTER	docIDs	...		283047		283154		283159		283202	...
	gaps				107		5		43		...
ARACHNOCENTRIC	docIDs	252000		500100							
	gaps	252000	248100								

Variable length encoding

- Aim:
  - For ***arachnocentric***, we will use ~20 bits/gap entry.
  - For ***the***, we will use ~1 bit/gap entry.
- If the average gap for a term is *G*, we want to use ~$\log_2 G$ bits/gap entry.
- Key challenge: encode every integer (gap) with about as few bits as needed for that integer.
- This requires a *variable length encoding*
- Variable length codes achieve this by using short codes for small numbers

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Inverted File Index

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- Ranked retrieval
- Performance measures
- Take-home messages

Ranked retrieval

- Thus far, our queries have all been Boolean.
  - Documents either match or don't.
- Good for expert users with precise understanding of their needs and the collection.
  - Also good for applications: Applications can easily consume 1000s of results.

Ranked retrieval

- Thus far, our queries have all been Boolean.
  - Documents either match or don't.
- Good for expert users with precise understanding of their needs and the collection.
  - Also good for applications: Applications can easily consume 1000s of results.
- Not good for the majority of users.
  - Most users incapable of writing Boolean queries (or they are, but they think it's too much work).
  - Most users don't want to wade through 1000s of results.
    - This is particularly true of web search.

Problem with Boolean search: feast or famine

- Boolean queries often result in either too few (=0) or too many (1000s) results.
- Query 1: "*standard user dlink 650*" → 200,000 hits
- Query 2: "*standard user dlink 650 no card found*": 0 hits
- It takes a lot of skill to come up with a query that produces a manageable number of hits.
  - AND gives too few; OR gives too many

Ranked retrieval models

- Rather than a set of documents satisfying a query expression, in ranked retrieval, the system returns an ordering over the (top) documents in the collection for a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language
- In principle, there are two separate choices here, but in practice, ranked retrieval has normally been associated with free text queries and vice versa

Feast or famine: not a problem in ranked retrieval

- When a system produces a ranked result set, large result sets are not an issue
  - Indeed, the size of the result set is not an issue
  - We just show the top k (≈ 10) results
  - We don't overwhelm the user

- Premise: the ranking algorithm works

Scoring as the basis of ranked retrieval

- We wish to return in order the documents most likely to be useful to the searcher
- How can we rank-order the documents in the collection with respect to a query?
- Assign a score – say in [0, 1] – to each document
- This score measures how well document and query "match".

Take 1: Jaccard coefficient

- A common measure of overlap of two sets *A* and *B*
- jaccard*(A,B)* = $|A \cap B| / |A \cup B|$
- jaccard*(A,A)* = 1
- jaccard*(A,B)* = 0 if $A \cap B = 0$
- *A* and *B* don't have to be the same size.
- Always assigns a number between 0 and 1.

Jaccard coefficient: Scoring example

- What is the query-document match score that the Jaccard coefficient computes for each of the two documents below?
- Query: *ides of march*
- Document 1: *caesar died in march*
- Document 2: *the long march*

Issues with Jaccard for scoring

- It doesn't consider *term frequency* (how many times a term occurs in a document)
- Rare terms in a collection are more informative than frequent terms. Jaccard doesn't consider this information
- We need a more sophisticated way of normalizing for length

Query-document matching scores

- We need a way of assigning a score to a query/ document pair
- Let's start with a one-term query
- If the query term does not occur in the document: score should be 0

Query-document matching scores

- We need a way of assigning a score to a query/ document pair
- Let's start with a one-term query
- If the query term does not occur in the document: score should be 0
- The more frequent the query term in the document, the higher the score (should be)
- We will look at a number of alternatives for this.

Binary term-document incidence matrix

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Each document is represented by a binary vector $\in \{0,1\}^{|V|}$

Term-document count matrices

- Consider the number of occurrences of a term in a document:
  - Each document is a count vector in $\mathbb{N}^v$: a column below

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	157	73	0	0	0	0
Brutus	4	157	0	1	0	0
Caesar	232	227	0	2	1	1
Calpurnia	0	10	0	0	0	0
Cleopatra	57	0	0	0	0	0
mercy	2	0	3	5	5	1
worser	2	0	1	1	1	0

Bag of words model

- Vector representation doesn't consider the ordering of words in a document
- *John is quicker than Mary* and *Mary is quicker than John* have the same vectors
- This is called the bag of words model.
- In a sense, this is a step back: The positional index was able to distinguish these two documents.

Term frequency tf

- The term frequency $tf_{t,d}$ of term *t* in document *d* is defined as the number of times that *t* occurs in *d*.
  - Note: Frequency means count in IR
- We want to use tf when computing query-document match scores. But how?

Term frequency tf

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  - Note: Frequency means count in IR
- We want to use tf when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
- Relevance does not increase proportionally with term frequency.

Log-frequency weighting

- The log frequency weight of term t in d is

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d}, & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

- 0 → 0, 1 → 1, 2 → 1.3, 10 → 2, 1000 → 4, etc.
- Score for a document-query pair: sum over terms *t* in both *q* and *d*:
- score $= \sum_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$

- The score is 0 if none of the query terms is present in the document.

Rare terms are more informative

- Rare terms are more informative than frequent terms
  - Recall stop words
- Consider a term in the query that is rare in the collection (e.g., *arachnocentric*)
- A document containing this term is very likely to be relevant to the query *arachnocentric*
- → We want a high weight for rare terms like *arachnocentric*.

Collection vs. Document frequency

- Collection frequency of *t* is the number of occurrences of *t* in the collection
- Document frequency of t is the number of documents in which t occurs
- Example:

Word	Collection frequency	Document frequency
insurance	10440	3997
try	10422	8760

- Which word is for better search (gets higher weight)

idf weight

- df_t is the document frequency of t: the number of documents that contain t
  - df_t is an inverse measure of the informativeness of t
  - $df_t \leq N$
- We define the idf (inverse document frequency) of t by

$$idf_t = \log_{10}(N/df_t)$$

  - We use log (N/df_t) instead of N/df_t to "dampen" the effect of idf.

idf example, suppose N = 1 million

term	df_t	idf_t
calpurnia	1	6
animal	100	4
sunday	1,000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

$$\text{idf}_t = \log_{10}(N/\text{df}_t)$$

There is one idf value for each term t in a collection.

Effect of idf on ranking

- Does idf have an effect on ranking for one-term queries, like
  - iPhone

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- idf has no effect on ranking one term queries
  - idf affects the ranking of documents for queries with at least two terms
- For the query capricious person, idf weighting makes occurrences of capricious count for much more in the final document ranking than occurrences of person.

tf-idf weighting

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = \log(1 + \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
  - Note: the "-" in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Score for a document given a query

$$\text{Score}(q,d) = \sum_{t \in q \cap d} \text{tf.idf}_{t,d}$$

- There are many variants
  - How "tf" is computed (with/without logs)
  - Whether the terms in the query are also weighted
  - …

TF-IDF as Cosine Distance

query vector: IDF $\langle w_{q,t_1}, w_{q,t_2}, \ldots, w_{q,t_k} \rangle$

document vector: TF $\langle w_{d,t_1}, w_{d,t_2}, \ldots, w_{d,t_k} \rangle$

$$w_{q,t} = \ln\left(1 + \frac{N}{f_t}\right) \qquad w_{d,t} = 1 + \ln f_{d,t}$$

$$W_d = \sqrt{\sum_t w_{d,t}^2} \qquad W_q = \sqrt{\sum_t w_{q,t}^2}$$

$$S_{q,d} = \frac{\sum_t w_{d,t} \cdot w_{q,t}}{W_d \cdot W_q}.$$

Outline:
Inverted File Index

- Information retrieval
- Index construction & compression
- Ranked retrieval
- Performance measures
- Take-home messages

Evaluating an IR system

- Note: **user need** is translated into a **query**
- Relevance is assessed relative to the **user need,** *not* the **query**
- E.g., Information need: *My swimming pool bottom is becoming black and needs to be cleaned.*
- Query: ***pool cleaner***
- Assess whether the doc addresses the underlying need, not whether it has these words

Unranked retrieval evaluation: Precision and Recall

- **Binary assessments**

Precision: fraction of retrieved docs that are relevant = P(relevant|retrieved)

Recall: fraction of relevant docs that are retrieved = P(retrieved|relevant)

	Relevant	Nonrelevant
Retrieved	true positive (tp)	false positive (fp)
Not Retrieved	false negative (fn)	true negative (tn)

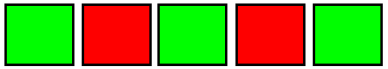
- Precision P = tp/(tp + fp)
- Recall R = tp/(tp + fn)

Rank-Based Measures

- Binary relevance
  - Precision@K (P@K)
  - Mean Average Precision (MAP)
  - Mean Reciprocal Rank (MRR)
- Multiple levels of relevance
  - Normalized Discounted Cumulative Gain (NDCG)

Precision@K

- Set a rank threshold K
- Compute % relevant in top K
- Ignores documents ranked lower than K
- Ex:



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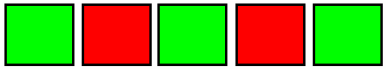
  - Prec@3 of 2/3



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- Ex:
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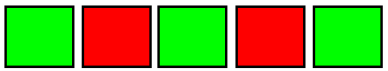
  - Prec@4 of 2/4



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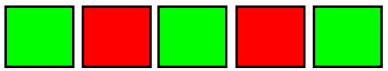

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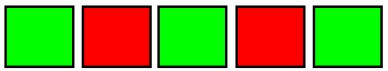
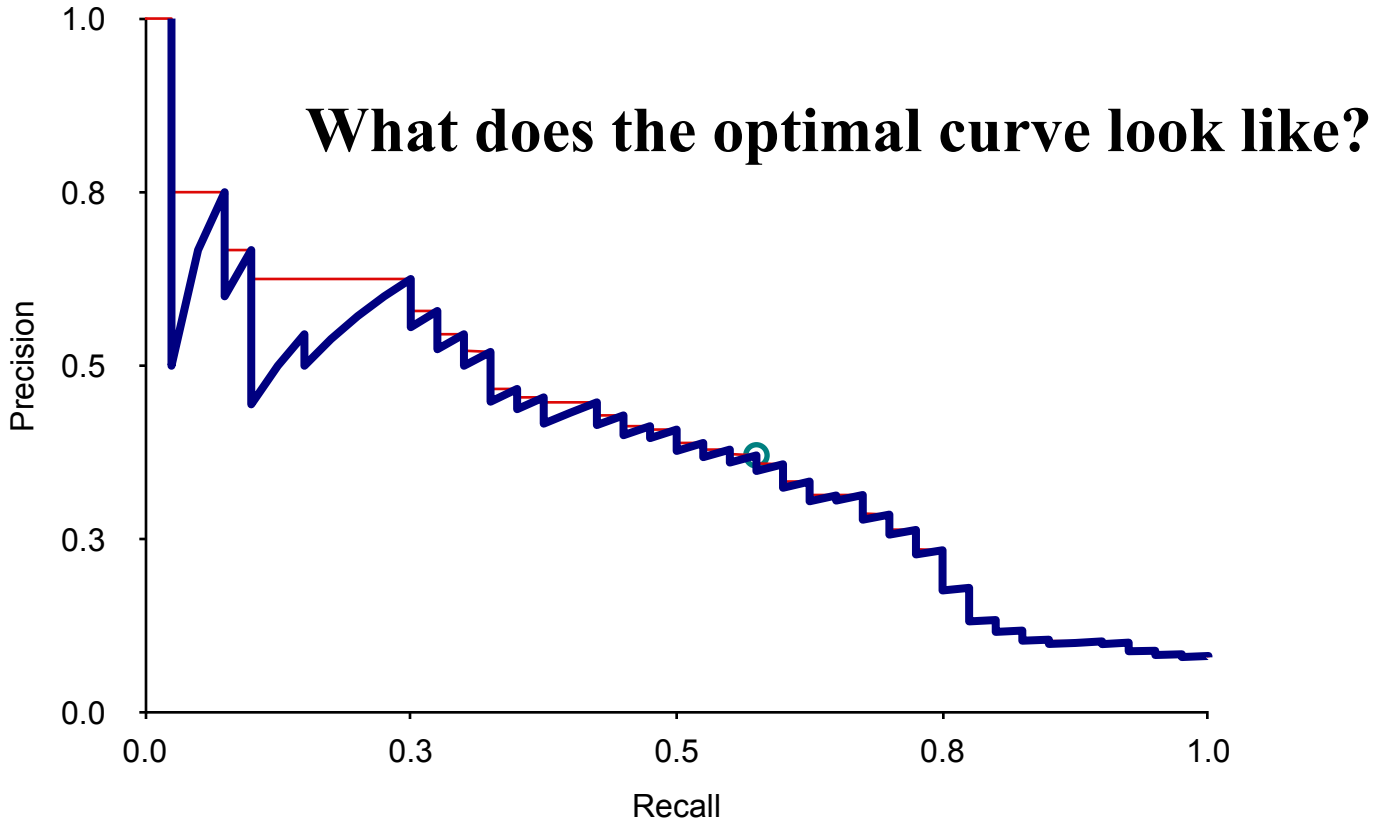
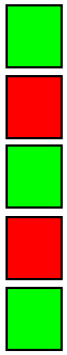


- In similar fashion we have Recall@K

A precision-recall curve



Mean Average Precision

- Consider rank position of each ***relevant*** doc
  - K_1, K_2, … K_R
- Compute Precision@K for each K_1, K_2, … K_R
- Average precision = average of P@K
- Ex:  has AvgPrec of
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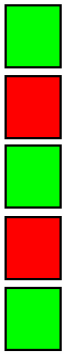
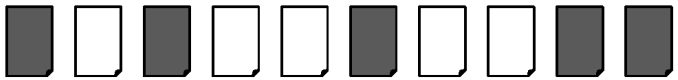
- Ex:  has AvgPrec of $\frac{1}{3}\cdot\left(\frac{1}{1}+\frac{2}{3}+\frac{3}{5}\right)\approx 0.76$
- MAP is Average Precision across multiple queries/ rankings

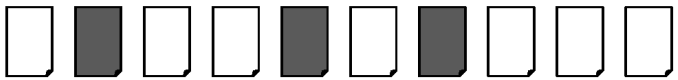
MAP


= relevant documents for query 1

Ranking #1 

Recall	0.2	0.2	0.4	0.4	0.4	0.6	0.6	0.6	0.8	1.0
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5


= relevant documents for query 2

Ranking #2 

Recall	0.0	0.33	0.33	0.33	0.67	0.67	1.0	1.0	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.33	0.43	0.38	0.33	0.3

$$average\ precision\ query\ 1 = (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$$
$$average\ precision\ query\ 2 = (0.5 + 0.4 + 0.43)/3 = 0.44$$

$$mean\ average\ precision = (0.62 + 0.44)/2 = 0.53$$

Mean average precision

- If a relevant document never gets retrieved, we assume the precision corresponding to that relevant doc to be zero
- MAP is macro-averaging: each query counts equally
- Now perhaps most commonly used measure in research papers

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Mean average precision

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- MAP is macro-averaging: each query counts equally
- Now perhaps most commonly used measure in research papers
- Good for web search?
- MAP assumes user is interested in finding many relevant documents for each query
- MAP requires many relevance judgments in text collection

Discounted Cumulative Gain

- Popular measure for evaluating web search and related tasks

- Two assumptions:
  - Highly relevant documents are more useful than marginally relevant documents
  - the lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Discounted Cumulative Gain

- Uses *graded relevance* as a measure of usefulness, or *gain,* from examining a document
- Gain is accumulated starting at the top of the ranking and may be reduced, or *discounted*, at lower ranks
- Typical discount is 1/log *(rank)*
  - With base 2, the discount at rank 4 is 1/2, and at rank 8 it is 1/3

Summarize a Ranking: DCG

- What if relevance judgments are in a scale of [0,r]? r>2
- Cumulative Gain (CG) at rank n
  - Let the ratings of the n documents be r_1, r_2, …r_n (in ranked order)
  - CG = $r_1+r_2+\ldots r_n$
- Discounted Cumulative Gain (DCG) at rank n
  - DCG = $r_1 + r_2/\log_2 2 + r_3/\log_2 3 + \ldots r_n/\log_2 n$
    - We may use any base for the logarithm

Discounted Cumulative Gain

- *DCG* is the total gain accumulated at a particular rank *p*:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}$$

- Alternative formulation:

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log(1+i)}$$

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  - used by some web search companies
  - emphasis on retrieving highly relevant documents

DCG Example

- 10 ranked documents judged on 0–3 relevance scale:

  3, 2, 3, 0, 0, 1, 2, 2, 3, 0

- discounted gain:

  3, 2/1, 3/1.59, 0, 0, 1/2.59, 2/2.81, 2/3, 3/3.17, 0

  = 3, 2, 1.89, 0, 0, 0.39, 0.71, 0.67, 0.95, 0

- DCG:

  3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61

NDCG for summarizing rankings

- Normalized Discounted Cumulative Gain (NDCG) at rank *n*
  - Normalize DCG at rank *n* by the DCG value at rank *n* of the ideal ranking
  - The ideal ranking would first return the documents with the highest relevance level, then the next highest relevance level, etc
- Normalization useful for contrasting queries with varying numbers of relevant results
- NDCG is now quite popular in evaluating Web search

NDCG - Example

4 documents: d_1, d_2, d_3, d_4

i	Ground Truth		Ranking Function$_1$		Ranking Function$_2$	
	Document Order	r_i	Document Order	r_i	Document Order	r_i
1	d4	2	d3	2	d3	2
2	d3	2	d4	2	d2	1
3	d2	1	d2	1	d4	2
4	d1	0	d1	0	d1	0
	$NDCG_{GT}$=1.00		$NDCG_{RF1}$=1.00		$NDCG_{RF2}$=0.9203	

$$DCG_{GT} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.6309$$

$$DCG_{RF1} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.6309$$

$$DCG_{RF2} = 2 + \left(\frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.2619$$

$$MaxDCG = DCG_{GT} = 4.6309$$

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Inverted File Index

- Information retrieval
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Take-Home Messages

- Information retrieval:
  - Answering queries from unstructured databases.
- Inverted file index:
  - Mapping from items to posting lists of documents.
  - Sorted, frequency of appearance, positions.
- Ranked retrieval:
  - Measure relevance between query and document by TF-IDF.
- Performance measures:
  - Precision, recall, MAP, NDCG…

Thanks for your attention!
Discussions?

Reference

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